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Does the number of social network followers relate to corporate value?

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Does the number of social network followers relate to corporate value?

Patrick Mauder

TITLE PAGE

Submitted in total fulfilment of the requirements for the degree of

Master of Philosophy

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Bond Business School

Professor Keith Duncan and Assistant Professor Jan Hollindale

ABSTRACT

Little insight is provided in the academic literature as to whether or not investment in social media adds value. Social media is growing in user numbers globally with user numbers reaching billions. Firms take note of this development and seek to partake in the benefits of investing into social media. Yet what remains difficult is to quantify the financial benefits for firms from social media. Prior research found uncertainty for small and large firms on whether value is derived from the information present on social media and the access to the large number of users. Based on a sample of 74 listed Australian firms for an observation period of 30 days of June 2016, the study seeks to expand the body of literature by exploring the relationship between social media activity and corporate value.

I find that social media network follower numbers provide a link, albeit not a very strong one, between social media network activity and corporate value. The results contribute to the literature and add to the understanding for firms on the financial impact of social media network followers. Limitations and future research opportunities are discussed to further deepen the understanding and close the gap in the current knowledge.

Keywords – social media, firm performance, Facebook, LinkedIn, Twitter, social media value model

DECLARATION BY AUTHOR

This thesis is submitted to Bond University in fulfilment of the requirements of the degree of Master of Philosophy.

This thesis represents my own original work towards this research degree and contains no material that has previously been submitted for a degree or diploma at this University or any other institution, except where due acknowledgement is made.

Patrick Mauder

The research associated with this thesis received ethics approval from the Bond University Human Research Ethics Committee, ethics application number 0000015603.

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Finally, my thanks go to my family in Australia, my wife Anna Mauder and my daughter Angelina Mauder. Your belief in me and unwavering love has helped me tremendously to see this project through to the end.

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ABBREVIATIONS

Analysis of Variance	ANOVA
Australian Real Estate Investment Trusts	A-REITs
Australian Stock Exchange	ASX
Business to Business	B2B
Business to Consumer	B2C
Capital Asset Pricing Model	CAPM
Chief Executive Officer	CEO
Chief Financial Officer	CFO
Corporate Social Networks	CSN
Cumulative Abnormal Return	CAR
Earnings Before Interest and Tax	EBIT
Efficient Market Hypothesis	EMH
Fixed Effects Model	FEM
Global Industry Classification Standards	GICS
Global Reporting Initiative	GRI
International Integrated Reporting Council	IIRC
Mixed Ordinary Least Squares	MOLS
Random Effects Model	REM
Return on Assets	ROA
Return on Investment	ROI
Small to Medium sized Enterprises	SME
Social Media Value	SMV
Standard and Poor	S&P
User-Generated Content	UGC
Word Of Mouth	WOM

Chapter 1. MOTIVATION

The academic literature provides little insight into whether or not investment in social media adds value. This thesis addresses this gap and is motivated by the challenges faced by professionals, namely:

"…, *there's no single measure of social media's financial impact, and many companies find that it's difficult to justify devoting significant resources—financial or human—to an activity whose precise effect remains unclear"* (Divol et al., 2012).

" … the CEO and CFO are demanding evidence of potential ROI (of social media) before allocating dollars to marketing efforts" (Hoffman & Fodor, 2010).

"Measuring ROI" was the most commonly cited challenge; 60% of respondents included it as one of the top three most challenging aspects of their social media program " (Headley, 2015).

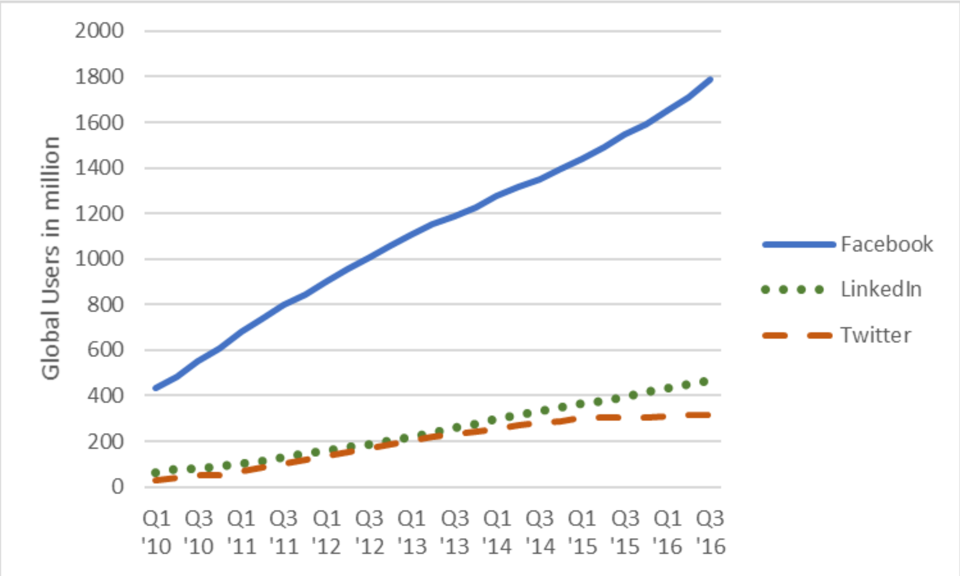
These challenges faced by business professionals, together with the lack of academic enquiry into the impact of social media on corporate value, provide motivation for this study.

1.1 GROWING USE OF SOCIAL MEDIA NETWORKS

Large and growing social media user numbers seem to indicate an importance for organizations to partake in social media. Consequently, social media is considered an area of potential value for business, yet quantifying the benefits of investing in social media is difficult. The popularity of social media as a communication channel of the masses suggests an opportunity for firms to reach a large number of current and potential customers. Further, firms may obtain valuable insights from users' posts to those sites, utilise this knowledge in their production and marketing decisions, and subsequently increase the financial performance of the firm, creating value for shareholders.

Several social media platforms have gained global prominence, for example, Facebook, LinkedIn and Twitter. Figure 1 depicts the growth of these three social media networks between 2010 and 2016, at the end of which period global social media network user numbers exceeded 1.788 billion for Facebook (statista.com, 2016a), close to 467 million for LinkedIn (statista.com, 2016b) and 317 million for Twitter (statista.com, 2016c).

FIGURE 1 – GLOBAL SOCIAL NETWORK USERS



Source: statista.com

In Australia, the number of social media network users has been estimated as 14 million, 3.6 million and 2.8 million respectively for Facebook, LinkedIn and Twitter as at August 2015 (Cowling, 2015).

Investors and other firm stakeholders may find it useful to track the general sentiment and extent of social media attention on a firm and its operations. These types of data may provide information about current and potential customers' needs and intentions to transact with that firm. Accordingly, investors and other stakeholders may consider this knowledge relevant when making future investment decisions. Consequently, social media network user numbers may be value-relevant.

This study examines whether social media network activity is a factor in determining corporate value. Social media network follower numbers for the purpose of this study refers to Facebook page 'likes' as well as LinkedIn and Twitter account follower numbers.

1.2 BUSINESS CHALLENGES

The issue highlighted by managers in the introductory quotations is the lack of a clear understanding of the return social media generates for business entities. This deficit is one of the challenges faced by managers and this section discusses this and documents other challenges.

Research has found that uncertainty of the benefits of investing in social media is an issue for firms, regardless of size. Small to medium sized enterprises (SMEs) were found to report ambiguity of the benefits of investing into social media in a study by Kadam and Ayarekar (2014). These researchers found that while most respondents were aware of social media and considered social media to have a large impact on their firm, the majority also confirmed their understanding of social media was only basic or below basic.

Firms intend to increase their investments in social media (Divol et al., 2012) but struggle to justify the investments. Hence, it is important to understand the impact of social media on financial performance to allow better justification for managers' social media spending decisions. Social media measures represent non-financial indicators which have the potential to represent a leading factor of future financial performance (Cohen et al., 2012; Du & Jiang, 2015). Managers generally consider that non-financial measures provide useful information of performance of a non-monetary value, which eventually leads to enhanced financial performance. The usefulness of non-financial measures has been researched extensively; see, for example, the work of Kaplan and Norton (1992), Ittner and Larcker (1998), Blankespoor et al. (2014), and Schulze et al. (2012). Non-financial performance measures are claimed to provide a more complete evaluation of future firm performance as opposed to financial performance measures alone. The use of the balanced scorecard by numerous firms worldwide is offered in support of these claims. Arguably, social media-related measures are reflective of a firm's brand and reputation in the product market, which is likely to impact on the firm’s future financial performance. Hence managers require an understanding of social media-related measures to better evaluate future financial performance.

While the balanced scorecard is predominantly an internal reporting device used to measure and monitor performance against strategic objectives, recent developments in external reporting also include the disclosure of non-financial performance information to shareholders and other stakeholders. Various reporting frameworks have been developed in recent times that provide interested stakeholders with financial and non-financial firm performance, for example Triple Bottom Line (Elkington & Burke, 1987) and the Global Reporting Initiative (GRI, 2017). These are concerned with extending financial performance reporting to include disclosure on non-financial performance, typically associated with providing accountability and transparency of firm performance on sustainability and human relations activities. Other reporting frameworks, for example the Connected Reporting Framework (Adams & Simnett, 2011) and the Integrated Reporting framework (IIRC, 2010), focus on disclosing how organisational activities connect with corporate strategy and management, and lead to the creation of value over the short, medium and long term. Non-financial performance in these recent reporting developments is considered a significant contributor to value creation for firms and allows investors to make an assessment on the financial sustainability of the firm (Eccles & Krzus, 2010).

The Integrated Reporting ethos is based on the premise that a firm’s value is created from six capitals (financial, manufactured, intellectual, human, social and relationship, and natural) (IIRC, 2015a). This concept informs this study. Social media measures might link through to firm value. Firm value is represented by the share price which is based on the present value of future expected cash flows (Kothari, 2001). Future expected cash flows are in part influenced by non-financial factors, and social media measures such as social media network follower numbers might provide a signal with corporate value implications.

The importance of managers having a better understanding of the impact social media has on corporate value is one of the motivations for this study. The following section provides a brief overview of several social media studies and highlights the limited depth of relevant research.

1.3 PRIOR RESEARCH

Social media has been a topic of research, yet a gap in the understanding of social media network activity implications for corporate value still exists. This section discusses several studies and highlights the limited depth of relevant research.

Managers consider social media platforms for transforming their firm in strategically important areas, for example, customer engagement, brand management, as well as business processes (Luo et al., 2013). Customer engagement, for example, is significantly improved through social media network activity (Du & Jiang, 2015). Firms can communicate to customers and customers can respond, and in a rapid and low cost manner. Social media facilitates customer inputs to a significantly larger extent than traditional media such as newspapers, radio and TV, which is further intensified due to the rapid growth of social media (Tirunillai & Tellis, 2012). While social media has received attention from academics and firms, reflecting its importance, the rapid growth of users is likely to increase the focus further. For example, Tirunillai and Tellis's (2012) study examines customer inputs, specifically content generated by users of product rating and product review sites, finding a correlation to corporate value. However, in this study the scope and focus on the researched social media platforms is limited.

Firms assume a benefit from the increased customer engagement on social media and hence allocate resources to social media management and intend to increase this resource allocation in the future (Divol et al., 2012). However, the expected benefits of this type of management have only been researched to a limited extent and hence no detailed validation of those assumptions have been provided.

Furthermore, some studies isolate components of social media network activity and establish several performance outcomes, such as corporate value and abnormal return for firms in the United States of America and Spain (Du & Jiang, 2015; Luo et al., 2013; Paniagua & Sapena, 2014; Tirunillai & Tellis, 2012). Those outcome measures explain the impact of product rating, product review, and social media network activity on corporate value in limited settings.

1.4 MOTIVATION FOR RESEARCH

This research is exploratory in nature. It is targeted at improving the understanding of the effect of social media network activity on corporate value of publicly listed companies, and is motivated by the paucity of research. This study intends to provide insights for managers regarding social media network activity levels and fill a gap in the literature. As such, to the author's knowledge this study is the first in an Australian context that seeks to link social media network activity to corporate value. Due to lack of consistent research, managers lack sufficient direction on increasing resource allocation for social media management and are uncertain about the resultant effect of their investment towards this venture (Divol et al., 2012; Hoffman & Fodor, 2010). The aim is to provide guidance to managers on value enhancement with respect to social media network follower numbers.

Some managers argue that the benefits of calculating traditional accounting performance indicators, such as ROI, are not as relevant to social media than other more marketing focused performance measurements (Hoffman & Fodor, 2010). Others consider calculating accounting returns for social media as quite feasible, yet alternate views are in evidence. Divol et al. (2012) report that some managers consider calculating a ROI for social media as being impractical, while other managers, for example, in a telecommunication firm, have established the ROI for social media network investment. This firm concluded that the ROI of social media investment was larger than the ROI of traditional media investment (Divol et al., 2012). It is unclear as to whether or not this example can be generalized without further research. Due to the lack of detailed information the statement cannot be verified nor the calculations duplicated in other settings. However, this case provides an example of the pressure professionals face to operationalise accounting performance measures for social media in addition to marketing performance measures. Note that this particular line of research is beyond the scope of this exploratory study.

Recent research has improved our understanding of the effects and importance of blogs and review sites (Tirunillai & Tellis 2012; Luo et al. 2013), as well as tagging on social media networking sites (Hyoryung & Kannan, 2014) on share market returns. Additionally, researchers have explored the impact on corporate value of the follower numbers on Facebook and Twitter in Spain, while a limited sample of research towards this direction has been provided in the United States (Paniagua & Sapena, 2014). In their study, Paniagua and Sapena (2014) examined this correlation in what the authors determine a “novel” market, being the Spanish market, and a “mature” market, being the United States. The authors observed that the followership and ‘likes’ (hereafter referred to as social media network followers) is significantly correlated with the share price of the firms. Interestingly, this correlation is only found once a “critical mass” (a turning point) has been established, and is initially negatively correlated.

It will be of advantage to both academics and professionals to explore the relationship between social media network activity and corporate value and the critical mass in an Australian context. Paniagua and Sapena (2014) find the relationship varies significantly between the two markets and between the networks. In the Spanish context the critical mass threshold for Facebook ‘likes’ is found to be between around 178,000 and 242,000 for individual corporations, while in the United States this number increases significantly to seventeen million. For Twitter the findings are similar. The critical mass for the Spanish sample is found to be between approximately 4,100 and 4,300 followers, while in the United States this number is around two hundred thousand followers. The variation between Facebook and Twitter suggests that an investment in Twitter might generate faster returns (Paniagua & Sapena, 2014). Examining the relationship between social media network activity and corporate value may inform social media resource allocation decisions as it provides guidance on its potential impact in the capital market.

The aim of this research is to examine the impact of social media network follower numbers on corporate share value in an Australian context. By replicating and extending Paniagua and Sapena (2014) in an Australian context this study seeks to establish the strength of the relationship, and the critical mass turning point. Furthermore, the study enables a comparison to the results established for the Spanish and US markets. In addition, building on prior research by Paniagua and Sapena (2014) this research (1) expands the scope of social media networks to include the professional network, LinkedIn, (2) expands the sample size to increase statistical validity and (3) examines two distinct groups of companies, those operating with a Business-to-Business (B2B) and those with a Business-to-Consumer (B2C) focus.

The exclusion of LinkedIn was noted as a limitation by Paniagua and Sapena (2014). LinkedIn is considered an influential social media platform (Hempel, 2013). LinkedIn reports to be the largest professional network (LinkedIn, 2015) with close to 400 million users globally (statista.com, 2016c) and 3.6 million users in Australia (Cowling, 2015). Its position as a professional network could indicate its usefulness for B2B as well as B2C relationships (LinkedIn, 2015).

Prior studies examining a relationship between social media and corporate value are based on relatively small samples. The study by Luo et al. (2013), is based on a sample of nine corporations, Tirunillai and Tellis (2012) examine 15 corporations and Paniagua and Sapena (2014) study 26 Spanish and nine American companies. This study expands on prior research by increasing the sample size to improve statistical validity and power.

Additionally, prior research focuses predominately on B2C firms (Luo et al., 2013; Tirunillai & Tellis, 2012) or do not differentiate between B2B and B2C firms (Du & Jiang, 2015; Paniagua & Sapena, 2014). The sample in this study includes firms from both groups. It is expected that B2C firms are more or are differently impacted by social media network activity than B2B firms as consumer focused firms appear to use social media networks more extensively than B2C firms (Brennan & Croft, 2012).

1.5 CHAPTER CONCLUSION

This study contributes to the understanding of the value-relevance of social media network activity for companies by exploring the relationship between social media network follower numbers and corporate value in an Australian context. This research is an initial study in a program of research aiming to investigate and advance knowledge further in a limited body of knowledge regarding the value-relevance implications of social media network activity.

While some research has covered the financial performance implications of social media (Du & Jiang, 2015; Luo et al., 2013; Paniagua & Sapena, 2014; Tirunillai & Tellis, 2012), to the author's knowledge, no study on the topic has been conducted in Australia. Furthermore, as social media networks appear to continuously expand in terms of user numbers, the importance for firms to understand these implications are likely to increase. Determining a relationship between social media network activity and corporate value will be useful to managers' understanding of the benefits of investing into this form of social media. For academia, this study contributes to the understanding of the relationship between social media network follower numbers as a signal for brand value and cumulative abnormal return as a proxy for corporate value.

Furthermore, this study is a robust extension of prior work as it expands the social media networks to include the professional network LinkedIn. Conducted in an Australian setting, the study increases the sample size to improve statistical validity and power. Finally, this study examines a sample with a clear distinction of business target product markets with two groups, one with a B2B focus and the other with a B2C focus, enabling analysis between the groups.

Chapter 2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

In this chapter, relevant literature is discussed and hypotheses are developed. The chapter commences by defining social media and its developments. Relevant prior social media research follows, and then a social media value (SMV) model is introduced with which to explain the theoretical relationship between social media network activity and corporate value. Further this chapter discusses and establishes links between social media network follower numbers and information diffusion, revealed preferences and talent acquisition, to brand value. A discussion of signalling theory then follows. Social and relationship capital, intellectual capital and human capital are then explained as the three capitals underpinning the SMV model and how they link to corporate value. A discussion on critical mass concludes Chapter 2.

2.1 SOCIAL MEDIA

The term *social media* appears to have different meanings to various groups (Kaplan & Haenlein, 2010). The Oxford dictionary (2015) defines social media as “Websites and applications that enable users to create and share content or to participate in social networking”. While this is not the only definition and it appears no single generally accepted definition exists, the definition provides a useful description of the term. In the academic literature, the term “social media” encapsulates the concept of user-generated content through electronic channels such as blogs, social networking sites and microblogs (Kaplan & Haenlein, 2010).

Social media is essentially an information market where information is created and distributed by many different players, from firms to individuals. Information and content is shared and distributed on social media, with various degrees of access to that information by social media participants. The popularity and volume of social media users and content is enabled through technology advances which have shifted the control over content on the internet.

Communication between individuals and firms has changed with technological advancements. Early internet sites were creator-driven in terms of content, which allowed the creators of those websites a level of control over content on the internet (Kaplan & Haenlein, 2010). Creators of those early internet sites would add the content without influence afforded to the consumers of that content (Kaplan & Haenlein, 2010). This is a one-to-many approach of communication as generally one source was publishing to a wide audience (McCann & Barlow, 2015). Other information about firms, such as newspaper articles, were also to some degree made available on the world wide web and firms through their public relations and marketing efforts, were able to exert some influence over the content of those newspaper articles (Kaplan & Haenlein, 2010). Hence, while the content of newspapers was generated by third parties and this content was published on the internet, the firms still maintained a level of control.

With the advancement of technology, the owner generated content of the early internet sites was expanded through user-generated content (UGC). User-generated content, largely enabled through Web 2.0, increased usage of social media significantly.[1] User-generated content is where the users produce the online content through blogs, videos, contributions to micro blogs and social media networks. UGC is how users interact on social media (Kaplan & Haenlein, 2010). Social media is a many-to-many approach to communication as many sources communicate with a wide audience through user-generated content (McCann & Barlow, 2015). Social media network follower numbers continue to grow significantly in part due to the development of mobile computing and smart phones (Kaplan & Haenlein, 2010). Following the development of the enabling technology, social media user numbers increased substantially and it appears this trend is set to continue. The focus of this study is on one branch of social media, social media networks, specifically three sites: Facebook, LinkedIn and Twitter.

2.2 PRIOR SOCIAL MEDIA RESEARCH

Prior studies have examined the use and importance of social media for various stakeholders. Nardi et al. (2004) explore the use of blogs, such as Twitter, and conclude the usage of blogs spans from personal opinion publication to commentary on

[1] The term web 2.0 is used to describe a set of technological advancements, such as Adobe Flash, RSS and AJAX (Asynchronous Java Script) (Kaplan & Haenlein, 2010; Tiago & Veríssimo, 2014).

contemporary issues. In more corporate focused studies, the effect of social media on customer opinion, purchase intention and sale of products through what is phrased as online “word of mouth” or WOM is investigated (Berger et al., 2010; Chevalier & Mayzlin, 2006; Dellarocas et al., 2007; Prendergast et al., 2010).

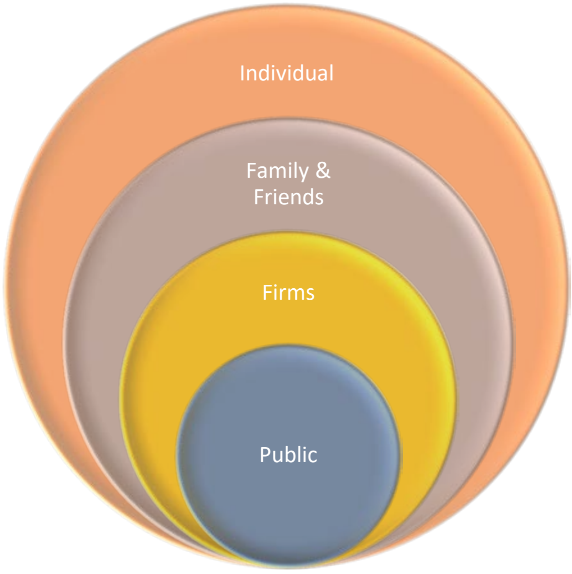
Firms take note of the rapid expansion of social media to communicate and manage the firm’s brand, as well as for more traditional marketing efforts (Correia et al., 2014; Tirunillai & Tellis, 2012). The increase of social media user numbers and the information generated on social media continues to increase that focus (Correia et al., 2014; Du & Jiang, 2015). Growth in social media network activity has been facilitated by technological advancements and increased access to the internet. The future growth of social media network activity might depend on further technological advances.

The marketing literature focuses on several objectives that social media may serve, ranging from brand evaluation, training systems, to different marketing focus between Business-to-Business (B2B) and Business-to-Consumer (B2C) target groups. Rollins et al. (2014) examine the use of blogs for sales training and find that this social media tool is useful learning tool. Swani et al. (2014) study the use of Twitter by B2B and B2C marketers of Fortune 500 companies and expand on the differences between those two groups. The authors find that the usage of social media by B2C is more emotional than functional. Hollenbeck and Kaikati (2012) study the use of Facebook to represent consumers’ actual and ideal identities, which in an extended sense could contribute to the influence of the signal individuals send (through their online identity). The ‘liking’ or following a commercial page could send a signal about an individual’s identification with that brand. Only a few marketing papers, such as Tirunillai and Tellis (2012), and Luo et al. (2013), correlate social media network activity to corporate value. Both studies investigated product review and rating sites. This study takes a different approach in that it focuses on social media networks, a different component of social media.

2.3 INFORMATION ACCESS IN SOCIAL MEDIA NETWORKS

Information access is a key component of the attractiveness of social media as the large number of users and the content generated by those users provide an attractive data source for firms. However, the access to information on social media networks is not the same for all participants. The limitation of access is enabled due to privacy settings on social media networks where users set access privileges, for example to show content to friends only, show selected parts of social media to selected groups, or to allow public access to content (Boyd & Hargittai, 2010). To visualize the various levels of access an information access model is proposed in Figure 2. The model depicts one view of the access levels the various participants in social media have to information. Individuals have access to all of their posted information. Family and friends seem to have access to a large portion of the individual's posted information. Firms have a more limited access to the information, and the public in general even less. The information access model in Figure 2 illustrates the information access by individuals as well as the narrowed information access and reach by firms. While the firm's access to information is less than complete, there is still information content and signals that can be assigned to levels of activity. The information available to firms provides interesting opportunities (Divol R, 2012).

FIGURE 2 – INFORMATION ACCESS THROUGH PRIVACY SETTINGS



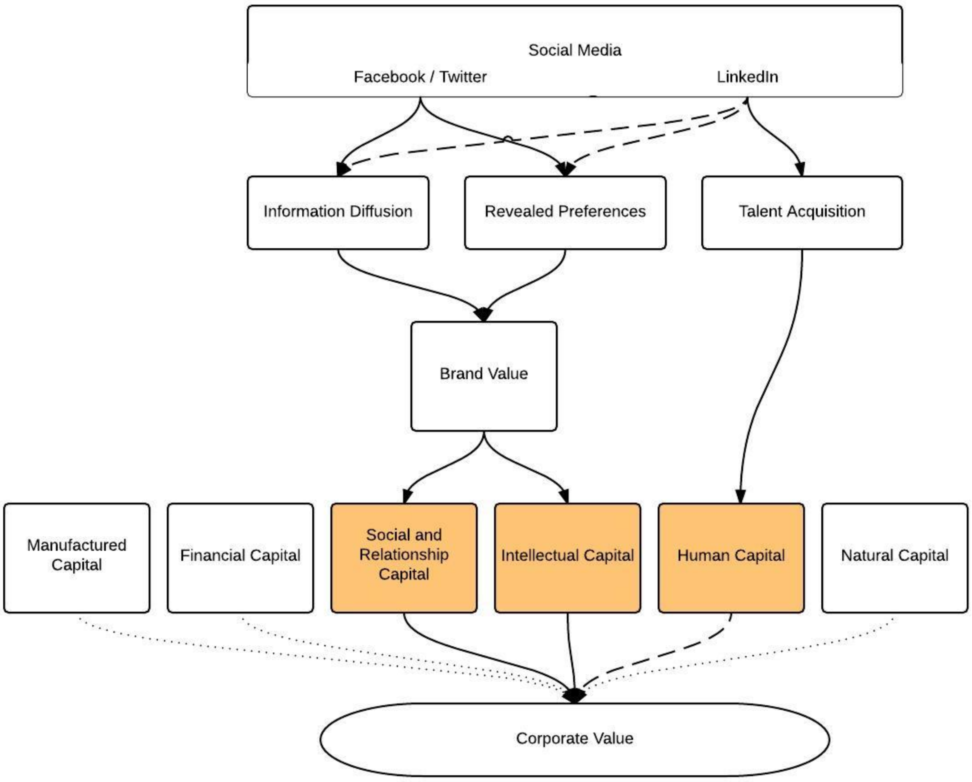
Social media networks are platforms within social media for individuals to create a profile, socialise, connect and access their preferred sites, including those from the firms they like. This study focuses on the effect on corporate value due to social media network activity by three groups. Group one are customers, who through social media channels, can communicate with and about firms, the firm's products, services and more generally about the brand. A second group are individuals as investors who access social media activity as a signal about firms' brand value to aid investment decisions. The final group are firms which, through social media, can communicate to and gain information about investors and customers.

In conclusion, social media users and UGC information are increasing in volume. Firms have access to some of that information and through investment in social media can increase the activity relevant to the firm. Access to that information can be valuable to firms for marketing and product development purposes. Furthermore, the activity on social media networks sends a signal about brand value to customers and investors. Chief Marketing Officers intend to increase investment into social media, yet the main challenge remains to determine returns obtainable from this investment (Divol et al., 2012; Hoffman & Fodor, 2010). The literature provides limited insights into this relationship. Clearer insights may be gained by examining whether social media network activity levels connect to corporate value. The following section introduces the social media value (SMV) model which provides guidance on the corporate value effect of social media network activity and expands the literature to assist decision-making about social media investments.

2.4 SOCIAL MEDIA VALUE MODEL

This section describes the social media value (SMV) model, depicted in Figure 3. Social media network follower numbers are conceptualised in the SMV model as providing a signal about the three capitals of social and relationship capital, intellectual capital and human capital, which are considered to be intangible assets which reflect in corporate value due to their implications for future corporate performance. The SMV model describes the linkage between social media network activity and corporate value and identifies three channels: information diffusion, revealed preferences and talent acquisition. In the model, those three channels affect corporate value through influencing shareholders' investment decisions by impacting their perceptions of the intangible value of three capitals: social and relationship capital, intellectual capital and human capital.

FIGURE 3 – SOCIAL MEDIA VALUE (SMV) MODEL



The SMV model conceptualises that social media network activity provides investors with improved access to relevant information and signals about brand value, social and relationship capital, intellectual capital, and human capital. Investors' perceptions regarding these intangible capitals impact corporate value as they influence their beliefs about a firm's future profitability and hence, their investment decisions. The capitals relate to intangible assets which are only to a limited extent shown on the balance sheet but which have significant influence on future financial performance.

Social media is mainly about information, which can be used for branding, intellectual property development and customer engagement. Hence the main effect of the model is the link between social media through information diffusion and revealed preferences to brand value and ultimately to corporate value. A strong brand is supported and reinforced by (1) the reach of the firm and its messages through the information diffusion channel and (2) by meeting customers' expectations and trends through revealed preferences (Beukeboom et al., 2015; Naylor et al., 2012). In this way, social media contributes to corporate value because managers use this non-financial information in their decision making with the objective to improve performance (for example more sales, better products). The secondary effect in the SMV model is the impact of talent acquisition through human capital on corporate value but this is expected to have a longer "wear-in" time (Luo et al., 2013, p. 146). Social media network followership then provides a signal on internally generated, unrecognised intangible assets, which has value implications and is the focus of the study.

Each component of the SMV model is expanded on in the following sections, which include a review of relevant research and theories, and distils hypotheses related to the SMV model for empirical testing

2.4.1 INFORMATION DIFFUSION

Information diffusion for the purpose of the SMV model describes the concept that information is more readily available, reaches a greater audience and provides an aggregate sentiment referred to as "wisdom of the crowd" (Luo et al., 2013).

Social media differs from traditional media due to the speed information can be made available, the speed this information reaches the audience, and the size of the audience (Luo et al., 2013). Interaction on social media is often instantaneous and can have a far reaching effect, not only on people's private opinions but also it seems on firms and markets (Du & Jiang, 2015; Luo et al., 2013; Paniagua & Sapena, 2014; Tirunillai & Tellis, 2012). While the earlier forms of social media had limited effects on firms, today's social media activity has an impact as explored by several studies such as Du and Jiang (2015), Hyoryung and Kannan (2014), Luo et al. (2013) and Tirunillai and Tellis (2012). For example Du and Jiang (2015) study the impact social media presence has on corporate value and find that social media presence relates to higher corporate value. The authors establish this relationship based on a sample of over 1,300 firms from the Standard and Poor's S&P 1,500 in the United States. Hyoryung and Kannan (2014) find that social media activity impacts brand measures such as brand familiarity, which in turn relates to unanticipated share return. Tirunillai and Tellis (2012) and Luo et al. (2013) find a correlation between social media activity and abnormal return.

Different types of information available through social media can impact firm value, such as leaked information, misinformation and firm disclosures (Paniagua & Sapena, 2014). When Google's 2012 earnings report was leaked through social media, the firm's performance was made available to the public ahead of the scheduled time and its share price was impacted. Some of this impact could possibly be contributed to the early availability of the information without the commentary usually provided at the time of release.

Misinformation can also impact markets. For example, the impersonation of a Russian interior minister in 2012 affected the global oil price (Paniagua & Sapena, 2014). Firm disclosures are another form of information which can be distributed through social media. Blankespoor et al. (2014) study the use of Twitter to disclose firm information and find that the use of Twitter results in a reduction in information asymmetry and improved share trading implications. Information asymmetry exists when one party has access to information while another party has not.

The impact of leaked earnings reports and misinformation is in line with the vast body of capital market research, in that all publicly available information is impounded in the share price (Kothari, 2001). The impact of misinformation on the share price should be corrected as soon as the misinformation is corrected (Wang et al., 2013). The implication is that social media content and activity is more timely and value relevant and should be captured in the share's market value.

The information on social media also expands from individuals' views to a cumulative view referred to as "wisdom of the crowd". Wisdom of the social media crowd supports a group sentiment about a product or firm that individuals accept as valid (Luo et al., 2013; Tirunillai & Tellis, 2012). Wisdom of the crowd in this context provides additional information of a perceived trend or agreement on social media networks (Surowiecki, 2005; Tirunillai & Tellis, 2012). Those additional information are a signal to users, and individuals trust collective sentiment more than professional recommendations and opinions partly due to the perceived impartiality of the wisdom of the crowd (Bartov et al., 2015). This concept has been supported by research, which has found wisdom of the crowd leads to better predictions such as earning and stock returns, in comparison to predictions from experts (Bartov et al., 2015).

Further, social media is a market for information where views about a firm are shared and reflected in mass sentiment and influence the social and relationship capital of the firm. Social media content reflects the values an organization shares with society (albeit this is limited to those present on social media). On the other hand, capital markets are about the collective view of information regarding a firm's future prospects and their impact on value. Hence both markets have broad numbers of participants and the dominant/collective view emerges. In the social media domain this is the collective view about the firm, while on capital markets it is the collective view about the value of the firm. As a consequence, the collective view about a firm's image, reputation and other attributes is relevant information for capital market participants and should be reflected in the value of the firm. The SMV model provides the linkage of one form of social media, social media networks, and its relationship with corporate value.

2.4.2 REVEALED PREFERENCES

Customers' preferences can be revealed through social media and this channel can provide clarity as to the identity and preferences of current customers and potential customers (Beshears et al., 2008). Research based on the social influence model (Kelman, 1958) suggests individuals 'like' or follow a firm due to their internalisation and identification with that firm (Leung & Tanford, 2015). According to this research, individuals 'like' a firm's social networking page due to the messages and image of the firm reconciling with the individual's own value system. Further, the action of 'liking' a page might also be motivated by the individual's desire to join or maintain a group membership (Leung & Tanford, 2015).

Observing customer preferences on social media together with the insight gained through access to customer identity and characteristics, can provide valuable input for firms and enable a focused effort, through resources allocation, to meet customer preferences (Luo et al., 2013). Firms can tailor products, services, and communication, based on revealed preferences and thus meet customer expectations and needs. The alignment of a brand's communication of the revealed preferences is of benefit to the firm as it is likely to increase the social media network follower numbers and, as a result, improve brand and marketing effectiveness (Leung & Tanford, 2015). Further, improved brand and marketing effectiveness can allow firms to improve sales performance and hence impact the firm's profitability, which is reflected in the share price. Beukeboom et al. (2015) confirm the link between social media 'likes', brand enhancement and the effect on purchase intention. The researchers evaluate the impact of Facebook 'likes' and expand prior research to find a causal relationship between 'liking' a Facebook page and brand evaluation leading to higher purchase intention. Revealed preferences, through brand improvement, increase social and relationship capital as well as improve intellectual capital. Customers' 'liking' generates a closer link between the individual and the firm as well as improves the firm's insights into those individuals (Vilnai-Yavetz & Tifferet, 2015).

2.4.3 TALENT ACQUISITION

In the SMV model, talent acquisition relates to the concept of corporate social media networking which refers to ties created between corporate staff through corporate social media networks (Paniagua & Sapena, 2014). Corporate social networks (CSNs) provide cost effective access to professionals, both internal and external to the firm. Professionals, rather than the public at large, are targeted by other professionals and network on those sites. The purpose of professional networking is to find future staff through communication with professionals as well as to share expertise and connect with potential customers (Brennan & Croft, 2012; Hempel, 2013; Paniagua & Sapena, 2014). It is acknowledged, however, that performance benefits flowing from employment of new talent sourced through CSNs may not materialise immediately. However, other activities conducted through CSNs, such as customer acquisition or knowledge sharing, could see results on a similar time basis as those of Facebook and Twitter, which is only a few days (Tirunillai & Tellis, 2012). Through sharing expertise, showcasing work, attracting talent and locating potential customers, the firm can leverage off CSNs to improve firm performance. Potential customers could come from a business-to-business arena, due to the professional focus of the networks. However, business-to-consumer opportunities might also be uncovered through firms targeting professionals with specialised products and services. Due the focus on talent acquisition, corporate social networking primarily increases human capital. Human capital is arguably the primary intangible asset of any firm as it is through this resource that most other capitals are created and developed or destroyed (Shepherd & Adams, 2014).

The corporate social network, LinkedIn, is included in this study. LinkedIn differs from other social media networks such as Facebook and Twitter through its specialised focus on professionals. Hempel (2013) suggests that LinkedIn "has emerged as one of the most powerful business tools on the planet" and the network's purpose has expanded beyond recruitment purposes to other purposes. LinkedIn is expected to primarily affect human capital with secondary effects on revealed preferences and information diffusion.

2.5 SIGNALLING THEORY

The SMV model focus is the signal provided by social media network activity and its impact on corporate value. Social media 'likes'/following is binary as people either select to 'like' or follow a firm or they don't. 'Liking' or following a firm in turn might provide a signal to others with implications for the firm (Paniagua & Sapena, 2014).

The signals can be examined through signalling theory. Signalling theory reflects on information asymmetry, when two parties (a sender and a receiver) are put into a situation with different levels of information access. This might be, for example, the case when the future value of a firm is of interest to a potential investor but private data are unavailable and hence impacts assessment accuracy due to not having access to the private data. The investor can attempt to overcome the information asymmetry by examining non-financial information. Social media network follower numbers are a signal a potential investor can utilise to make a judgement of the firm's social media presence as well as reasons and future implications for that presence. By interpreting the social media network follower numbers' signal the investor might draw conclusions, which may be about the brand value of the firm, and may or may not be accurate (Connelly et al., 2011). The interpretation of the signal would depend on the perceived authority and validity of the signal. For example, the certification of financial statements by a CEO, which depending on the perceived quality of that CEO signals the quality of financial statements which as a result impacts the share market (Zhang & Wiersema, 2009). In the SMV model, social media network activity levels link to corporate value due to the signal social media network follower numbers provide about brand value. Investors interpret this signal and assess the future earning capacity of the firm which is reflected in the returns generated.

Capital markets reflect available information and through signals such as social media network follower numbers, relevant information availability might be improved. Capital market research is based on the semi strong form of the efficient market hypothesis (EMH), which states that the share market adjusts rapidly to new public information and this public information is reflected in the share price (Fama, 1970). The strong form of the efficient market hypothesis would expand on the semi strong form to also incorporate private information. That is the markets under the strong form of market efficiency would adjust to all information which includes private information. To visualise, a pre-announcement share price impact in the case of impending mergers, as observed by Keown and Pinkerton (1981), would not be possible under the semi strong version of the EMH since the merger information is private in nature. Social media could be one channel to distribute this information intentionally or as a signal. Hence social media might distribute private information and thus might blur the line as to what information is private and what information remains private.

Information can be separated into two categories, either public or private (Fama et al., 1969). Private information, as mentioned earlier, is not available to the public at large while public information is. Through the recent use of social media, it seems that social media might release some information otherwise considered private. While individuals who are privy to private information might not release that private information directly, they might provide signals. For example, following a certain firm might provide a signal of the trustworthiness of that firm. Through social media, people can make choices to 'like' or follow certain articles, companies and individuals and thus provide a signal that could be interpreted by others to be related to some private information and might lead others to act on the information gleaned from that signal.

In the SMV model, social media network follower numbers provide a signal about brand value and make available information to a larger audience, reducing information asymmetry in the process.

2.6 THREE CAPITALS

The following section expands on each of the capitals included in the SMV model in Figure 3, specifically social and relationship capital, intellectual capital and human capital. These capitals are features of recent integrated reporting initiatives. Investors demand information of corporate performance that is typically not contained in financial reports. Integrated reporting seeks to develop firm reporting to fulfil this expanded demand for information, and thus communicate information about financial and non-financial performance. The essence of integrated reporting is that firms should report on six types of capital that create value: manufactured capital, financial capital, social and relationship capital, intellectual capital, human capital and natural capital (IIRC, 2015b). While manufactured capital, financial capital, and natural capital are important to firm value creation, they do not directly form part of the SMV model.

Eccles and Krzus (2010, p. 29) argue that the integrated report provides clarity on the relationship between non-financial performance and financial performance. The benefits of integrated reporting include internal benefits which lead to improved operational and strategic performance as well as external benefits, as mainstream investors gain access to non-financial information (Eccles & Saltzman, 2011). From an internal perspective the focus on the component capitals of integrated reporting is argued to guide managers' decision making focus towards more sustainable principles (Eccles & Saltzman, 2011). External investors on the other hand have access to information which aids the estimation of future performance and hence firm value, which in turn assists investors in their investment decisions, and enables a more efficient and productive allocation of capital (IIRC, 2015a).

While most firms interact with all capitals to some extent, the SMV model relies on three of the six capitals and thus discussions are limited to social and relationship capital, intellectual capital, and human capital. The concept underlying the SMV model is that the signal social media provides to investors by the provision of information across these three particular non-financial capitals, is suggested to be of interest to them because of their implications for future firm performance. The share price of a firm reflects current financial performance and an estimate of future financial performance (Francis, Olsson and Oswald, 2000). Hence additional information perceived to impact future financial performance ought to be useful in shareholders' investment decisions.

Social and relationship capital is defined as the capital of a firm in regards to relationships with stakeholders and society at large (IIRC, 2015a). The capital includes the norms, values and behaviours shared by the firm and society. It further includes relationships with stakeholders, as well as the brand image of the firm. In the SMV model the social and relationship capital is impacted by information diffusion as well as revealed preferences. Information diffusion assists firms to distribute information, which impacts the image stakeholders and society have of the firm (Paniagua & Sapena, 2014). Firms can maintain their legitimacy within society by utilising social media (Hsu, 2012). Further, by maintaining legitimacy and through revealed preferences insights, firms can manage the brand image effectively, which can improve social and relationship capital (Du & Jiang, 2015). In this study, a larger number of social media network followers is estimated to have a positive impact on social and relationship capital due to the wider reach of information.

Intellectual capital is the capital reflecting intangible assets based on knowledge such as intellectual property, for example, patents and trademarks (IIRC, 2015a). It further includes internal processes, systems and tacit knowledge. In the SMV model intellectual capital is impacted by revealed preferences. Revealed preferences provide insights for the firm regarding customers' evaluations of their products and services, as well as insights into customers' evaluations of their operations (Du & Jiang, 2015). The former allows for the improvement of products and services which form part of the firm's intellectual property. The latter provides information which the firm can use to improve processes and operations more broadly. In this study, a larger number of social media network followers is estimated to have a positive impact on intellectual capital due to the larger number of customers and potential customers available for analysis (Du & Jiang, 2015). Firms can anticipate challenges, for example, product/service complaints, by analysing social media content enabled through the followership. As a result, tailored solutions and changes to product and service offerings can be made to improve customer satisfaction, and customer loyalty. An improved brand image improves the probability that customers buy new products and resist competitors' products and services which improves the performance of the firm (Du & Jiang, 2015).

Human capital encompasses the value of employees to the firm, and their capabilities, motivations, experience and competencies (IIRC, 2015a). In the SMV model, corporate social media networking contributes to human capital. Corporate social networking is used to locate future talent and share expertise and hence improve capabilities, experience and competencies through recruitment, as well as through learning. It follows that a larger number of corporate social media network followers provides access to a larger talent pool and more expertise to enable learning in the firm.

2.7 THE LINK TO CORPORATE VALUE

The financial performance of a firm, as presented in the financial statements and announcements, is a significant component of information used to evaluate a firm's future cash flows and as a result, the share price (Kothari, 2001). However, various other items of information are considered by investors to make predictions on future cash flows and hence are reflected in the share price. Other sources, such as newspaper items, analysts' reports, rating agencies, and the use of those sources of information have been well documented in capital market literature, for example by Healy and Palepu (2001) and Amir and Lev (1996). More recently, capital market research is being supplemented by studies examining the impact of recent phenomena such as the effects of social media (Bartov et al., 2015; Du & Jiang, 2015; Hyoryung & Kannan, 2014; Luo et al., 2013; Paniagua & Sapena, 2014; Tirunillai & Tellis, 2012). Those studies provide for the impact of social media on the corporate value of the firm and reflect that social media matters to investors.

Social media is a communication channel where individuals share experiences including experiences with firms. Those experiences, coined word of mouth (WOM) can affect firm value indirectly through their effects on intangible assets such as the customer equity of the firm. Research shows that customer satisfaction and customer equity influence future expected cash flows, and thereby shareholder value (Bauer and Hammerschmidt 2005; Gupta 2009; Hanssens, Rust, and Srivastava 2009). Srivastava, Shervani, and Fahey (1998) propose that marketing assets, such as brand equity, create firm value through (1) an acceleration of cash flows, (2) an increase in the level of cash flows, (3) a decrease in the volatility and vulnerability of cash flows, and (4) an enhancement on the residual value of cash flows, which can ultimately be traced to customers. Online WOM through social media can affect consumer decisions to purchase products, thereby translating into future sales, cash flows, and stock performance at an aggregate level.

Customer equity is one of the prominent types of marketing asset measures (Rust et al., 2004) and researchers have examined its ability to generate future cash flows (Bick, 2009; Luo & Homburg, 2007; Tuli & Bharadwaj, 2009). Customer equity is recognized as a version of the principle of the present value of a stream of expected future cash flows and thus, is inherently related to a firm value (Srinivasan & Hanssens, 2009). Customer lifetime value is a further concept which links customer measures to corporate performance. Stahl et al. (2003) propose that customer lifetime value consists of four components: base potential (i.e., cash flow from purchasing products), growth potential (i.e., cash flow from cross-selling and up-trading), networking potential (i.e., cash flow from new relationships through WOM), and learning potential (i.e., cash flow from knowledge creation through interaction). They also argue that customer equity increases shareholder value by enhancing cash flows and reducing volatility of cash flows. Social media network follower numbers are proposed to be a signal of brand value and based on the research outlined above, link to corporate value.

Gupta et al. (2004) found that 1% improvement in customer retention increases firm value by 5% whereas 1% improvement in margin or acquisition costs generates improvements of only 1% and 0.1% in firm value, respectively. Kumar and Shah (2009) found that customer equity, which is determined by the customer lifetime value, can reliably predict the market capitalization of the firm, meaning that changes in customer equity influence the value of the firm. For example, higher incidents of negative WOM imply intense consumer dissatisfaction and thus, firms with higher negative WOM are likely to have a diminishing customer equity that reduces future cash flows (Riley et al., 2003).

This study proposes that social media network follower numbers impact the share price because they represent signals about social and relationship capital, intellectual capital and human capital which are intangible assets that lead to financial performance improvements. Based on the assumption of an efficient market, the share price reflects the future cash flows of a firm, assessed on all publicly available information, and discounted through a net present value calculation. Arguably, social media network follower numbers provide a signal to the market in relation to future expected cash flows from unrecognised intangible assets. This study contributes to the understanding about the impact of that signal on corporate value.

The consideration that social media is linked to corporate performance is based on the fact that large numbers of individuals spend large amounts of time on social media and provide information while engaging with social media (Luo et al., 2013). Further, customers and investors make decisions bearing in mind collective sentiment (Tirunillai & Tellis, 2012) and believe in social media sentiment (Bartov et al., 2015). Additionally, investors focus on more visible information, which infers that the more visible and accessible information is within the social media network, the more investors will focus on that information (Luo et al., 2013). Tirunillai and Tellis (2012) focussed on the impact of social media information on the share price. These authors reviewed how user-generated content is related to stock market performance and concluded that a statistically significant correlation exists. The sample in their study was examined for the volume as well as the inclination of the chatter on product review sites and the correlation to share market returns over a four-year period across six markets and fifteen firms. These researchers produced evidence of a correlation of negative sentiment with negative abnormal return. Furthermore, the volume of chatter was found to have the strongest positive affect on share returns.

This research explores the impact social media network activity has on corporate value in an Australian context to add to the understanding and literature in this field. Hence the following hypothesis is presented for testing:

H1: The social media network follower numbers on Facebook, LinkedIn and Twitter impact the share return of firms.

The nature of the firm's focus might provide further differentiation. While some firms serve predominantly a Business-to-Business (B2B) market, others operate in a Business-to-Consumer (B2C) market. Brennan and Croft (2012) find that B2B companies do not display the same usage of social media in comparison to B2C firms. Further, technology companies were predominately found to be active in social media. Prior research on product review sites focused primarily on B2C companies (Luo et al., 2013; Tirunillai & Tellis, 2012). Due to the predominant focus on individuals rather than firms, the relationship between social media network activity and corporate value might be stronger in B2C firms. Social media, specifically social media networking sites are used more extensively in B2C firms than in B2B firms (Swani et al., 2014). This study proposes to explore the difference between B2B and B2C firms and the relevant impact on corporate value.

The following hypothesis is therefore advanced for testing:

H2: The relationship between social media network follower numbers and share return is stronger for Business-to-Consumer firms than for Business-to-Business firms.

2.8 CRITICAL MASS

Prior research found that social media network activity has a significant correlation with corporate value but only once a critical mass in social media network followers has been reached (Paniagua & Sapena, 2014).The authors define the critical mass as the turning point at which social media follower numbers change from having a negative impact on share returns to having a positive impact. Further, Tirunillai and Tellis (2012) find that the volume of chatter on user-generated content sites is positively correlated with share returns. Their study focuses on product review and product rating sites. It examines exposed (those exposed to product reviews) companies and whether product discussions lead to an impact on the financial performance of the corporation. For example, in their study Nokia is selected as an exposed firm since its mobile phones revenue heavily impacts the firm's overall revenue. The authors do not comment on whether a certain volume of chatter is necessary to predict share returns. One of the potential reasons for this is the sample selected and the resulting exposure on user-generated content sites at the time of the study. Since one of the selection criteria for the study was that the firm must have rich data on user-generated content sites, it can be assumed that a certain threshold was applied. This threshold creates a bias of the sample towards firms heavily involved in social media and hence those firms could already be above the critical mass. The authors also did not comment on whether the volume impact was significantly different across the sample. Hence, whether the absolute volume of chatter influenced the strength of the impact on share market return is unknown.

Paniagua and Sapena (2014), on the other hand, establish a critical mass of social media network followers in their paper and find that this critical mass varies across different markets. In their study, the authors establish the critical mass to be between around 178,000 and 242,000 'likes' for Facebook and between about 4,100 and 4,300 followers for Twitter for the Spanish sample. For the United States sample those numbers increase significantly to more than seventeen million Facebook 'likes' and two hundred thousand Twitter followers (Paniagua & Sapena, 2014). The authors contribute the change in critical mass to the maturity of the market in terms of social media and the exposure of companies to social media. Another potential reason for the difference could be the size of the market and hence the customer base. It is likely that the companies in the United States sample, such as Apple, Ebay and Google have a significantly larger customer reach due to their size compared with the Spanish listed companies, resulting in larger numbers of ‘likes’ and followership. Providing insights into both the relationship as well as the critical mass in an Australian context is another focus of this study.

The point at which social media network activity is statistically significant to corporate value is considered of interest to both managers as well as academia. Managers require a justification for social media investments and related decisions. The point at which social media network activity correlates with corporate value would constitute useful information for social media decision making. In academia, knowing the critical mass would contribute to the gap in current literature around the correlation between social media and corporate value. Hence, the following hypothesis is presented for testing:

H3a: There is an impact of social media network follower numbers on corporate value after a critical mass is reached.

2.9 SOCIAL MEDIA NETWORK DIFFERENCE

This study expands prior research to cover three social media networks. Each of those networks has a different focus and hence differences in terms of impact on corporate value between the networks is likely. Facebook’s focus is networking of its users while Twitter’s predominant focus is microblogging, the continuous release of short messages on various topics (Smith et al., 2012). Facebook’s users are older, less educated and less wealthy than Twitter users (Molla, 2016). LinkedIn’s focus as a social media network is on professionals through networking, recruitment and information sharing (LinkedIn, 2015). Hence users on LinkedIn are predominantly professionals, a further difference to Facebook and Twitter. Paniagua and Sapena (2014) establish a difference between the social media networks and find that the critical mass for social media network follower numbers varies between Facebook and Twitter. Prior research has shown that the critical mass for Facebook is significantly higher than for Twitter. Due to the different focus in terms of use and users of the social media networks, the nature of the activity on each social media site means the strength and impact of each network might differ. The following hypothesis is presented for testing to gain this insight:

H3b: The effect of social media network follower numbers on corporate value varies among Facebook, LinkedIn and Twitter.

2.10 CHAPTER CONCLUSION

This chapter explores the literature leading to the development of the social media value (SMV) model, which depicts the theoretical relationship between social media, specifically the social media networks of Facebook, Twitter and LinkedIn, and corporate value. Social media network following is conceptualised in the SMV model as providing a signal about three types of intangible assets which, through their influence on investors' perceptions regarding future firm performance, are reflected in corporate value. Key concepts relevant to the SMV model are defined, the theoretical background discussed and relevant research on social media discussed. The three channels of information diffusion, revealed preferences and talent acquisition and their impact on three of the capitals important to corporate value creation are reviewed and established as the link between the social media network activity signal and corporate value. The three capitals included in the model are social and relationship capital, intellectual capital and human capital.

While the marketing literature has extensively researched social media it is emphasised that this study focuses on corporate value impacts from social media network follower numbers as opposed to evaluating social media in a marketing context. However, concepts from the marketing literature relevant for this study are incorporated where appropriate. The chapter concludes with a review of literature pertaining to corporate value and the development of four hypotheses for testing.

The hypotheses advanced for testing explore the relationship between social media network follower numbers and corporate value (H1); the difference between B2B and B2C firms in respect to their impact on corporate value through social media network follower numbers (H2); the establishment that a critical mass of social media network follower numbers is required before corporate value is affected (H3a); and the differing effects on corporate value among the three social media networks (H3b). The next chapter outlines the research design with which to test those hypotheses.

Chapter 3. RESEARCH DESIGN

3.1 INTRODUCTION

This chapter sets out the methods applied to examine the relationship between social media network activity and corporate value as proposed in the social media value (SMV) model. The chapter describes the empirical process used to quantify the relationship between social media network activity and corporate value. While some prior research such as Clarkson et al. (2006); Du and Jiang (2015); Luo et al. (2013); O'Connor (2013); Srinivasan and Hanssens (2009); Tirunillai and Tellis (2012) have empirically tested relationships between social media measures and corporate value, none so far have done this in an Australian setting using social media network follower numbers. This study builds on the body of knowledge by empirically testing Australian data using the SMV model. The sections following detail the sample and data used for this study, discusses panel data methodology, the use of univariate and multivariate analyses and concludes with a discussion about relevant tests to validate the assumptions underlying those methods.

3.2 SAMPLE

Australian listed companies are chosen as the target population because of the lack of prior research in relation to social media network activity and its relationship to corporate value in this setting. This study draws its sample from the Standard and Poor's (S&P) ASX200 companies listed on the Australian Securities Exchange (ASX) in June 2016. The S&P ASX200 represents the 200 largest companies in terms of market capitalisation (Carlin & Finch, 2011).

Global industry classification standards (GICS) were used to select the sample for testing. Given the nature of this study, 123 firms classified as belonging to the sectors of Australian Real Estate Investment Trusts (A-REITs), Energy, Financials, Financials excluding A-REITs, Health Care, Information Technology, Materials, Metals and Mining, Telecommunication Services and Utilities were excluded, leaving 77 companies classified as either Consumer Discretionary, Consumer Staples or

Industrials. Three companies were excluded from the sample due to mergers or takeovers, resulting in the final sample consisting of 74 firms as shown in Table 1.

TABLE 1 – SAMPLE SELECTION

Description	Number of firms
S&P ASX200	200
Firms not in Consumer Discretionary, Consumer Staples or Industrials	(123)
Firms delisted due to mergers or takeovers	(3)
Final Sample	74

The inclusion of firms with consumer focus and firms with business focus is based on the expectation that consumer focused firms utilise social media more than business-to-business focused firms. Thus, the inclusion of the industrial sector enables testing of hypothesis two to explore differences between B2B and B2C firms. Previous studies in this field have explored narrow samples such as computer hardware and software industries (Luo et al., 2013), IT industries, footwear and toys (Tirunillai & Tellis, 2012) or a selection of highly traded shares (Paniagua & Sapena, 2014). The sample for this study expands on prior research where research was limited to the most traded companies (Paniagua & Sapena, 2014) and social media exposed companies (Luo et al., 2013; Tirunillai & Tellis, 2012). Hence this study expands both sample size and sample scope to advance knowledge in this area.

3.3 DATA

Data on each sampled firms' daily social media network follower numbers, daily share prices, financial data, and news items were collected for the month of June 2016. The next sections provide the data collection processes.

3.3.1 SOCIAL MEDIA NETWORK FOLLOWER DATA

For the 74 selected companies in the final sample, the social media network follower data on official social media profiles on Facebook, LinkedIn and Twitter were extracted for analysis. The initial search commenced on each firm's home page. In instances where no links to the social media networks were displayed on the firm's home page, the investor relations and public relations pages of their websites were reviewed. Where no links were published on the firm's website, the firm or brand name was searched on search engines and in each social media network. Each profile identified in this way was accessed and verified to ensure it was the official firm-owned profile.

As Table 2 shows, some 36 firms were found to have an official presence on Facebook, 69 on LinkedIn, and 52 on Twitter.

TABLE 2 – FIRMS WITH SOCIAL MEDIA NETWORK PRESENCE

	Facebook	**LinkedIn**	**Twitter**
Firms with presence	36	69	52
Firms with no presence	38	5	22
Total	**74**	**74**	**74**

Several firms maintain more than one presence on social media network as presented in Table 3 below.

TABLE 3 - SOCIAL MEDIA NETWORK PROFILES

Social media network	**Social Media Profiles**			
	Total number of profiles	**1 per firm**	**2 per firm**	**3 or more per firm**
Facebook	59	29	1	6
LinkedIn	73	68	0	1
Twitter	112	34	3	15

Referring to Table 2 and Table 3, it is clear that while only 36 firms maintain Facebook profiles, seven firms have more than one profile, resulting in data for a total of 59 profiles. Some 69 firms keep a LinkedIn profile, one of which has three or more profiles on this network[2], giving a total of 73 profiles. Twitter presence is maintained by 52 firms. Some 34 of these hold single profiles, three firms have two profiles, and fifteen

[2] CIMIC Group.

firms in the sample have three or more profiles[3]. Thus data were collected for 112 Twitter profiles.

The social media analytics website, socialreport.com[4], was used to collect the daily follower data from these three social media networking sites for the thirty days of June 2016. Although funding limitations constrained access to this subscription-based social media analytics website to one month, the observation period nevertheless represents a full trading month and its span does not cover a major reporting period for listed companies which could otherwise be a confounding factor.

3.3.2 FINANCIAL DATA

In line with prior research, share market prices and relevant financial data were extracted from Bloomberg (Paniagua & Sapena, 2014). Daily opening and closing share prices, news counts, total assets, total liabilities, Earnings before Interest and Taxes (EBIT), the risk free rate, ASX200 index data (AXJO) and daily Fama French factors were collected from Bloomberg and the Dartmouth College website (French, 2017) for the 250 trading days leading up to the observation period as well as for the 30 days under observation. All data sets were matched to the relevant social media network follower data using the ASX listing code as the matching key.

3.3.3 DEPENDENT VARIABLE

The dependent variable for this study is cumulative abnormal return. Abnormal returns are calculated as the difference between raw returns and estimated returns using two different methods: CAPM and the Fama French three-factor model (Fama & French, 1993). Estimated returns are calculated by estimating the firm coefficients over the estimation period leading up to the observation window.

Various models have been used for time series data including the CAPM and the Fama French three-factor model (Liu, 2003). The Fama French three-factor model expands on

[3] Woolworths Ltd, for example, maintains six Twitter profiles.

[4] socialreport.com is a social media management platform, enabling the tracking of social media information of social media profiles cross a large range of social media networks.

the CAPM by adding a size and a value factor to the market risk factor included in the CAPM. Both models have in common that the parameters are estimated in an out-of-sample period. The assumption is that the parameters for the out-of-sample period do not change in comparison to the in-sample data. Given the sample data are collected over a 30-day period, concerns raised by Liu (2003, p. 22) that parameters developed in an out-of-sample period might change for sample periods of multiple years, are not applicable to this study due to the short observation period. Consistent with Tirunillai and Tellis (2012) and Luo et al. (2013), abnormal return is calculated by subtracting the expected return from the actual return.

The use of the Fama French three-factor model for calculating abnormal return is based on prior research such as Brailsford et al. (2012); Luo et al. (2013) and Tirunillai and Tellis (2012). Chiah et al. (2015) argue that the Fama French three-factor model has become the benchmark in asset pricing literature, outperforming the CAPM model. The Fama French model has also been tested in the Australian setting and has shown superior predictability power in comparison to the CAPM (Brailsford et al., 2012). It appears the inclusion of factors for size and book-to-market in the Fama French three-factor model improves the CAPM model not only in international studies but also in Australia. It is noted that the Australian studies calculate the Fama French factors for their studies.

To calculate the abnormal return, the Fama French factors are required. Prior studies (Luo et al., 2013; Tirunillai & Tellis, 2012) have extracted the factors from the database provided by Kenneth French on the Dartmouth College website. This study follows prior literature in obtaining the Fama French factors for Asia Pacific (excluding Japan) from the Dartmouth College website [5] . It is acknowledged that the factors published are calculated from a United States investors' point of view and hence are less useful in international applications than US domestic factors for US securities (Griffin, 2002).

5 Dr. Kenneth R. French is a professor of finance at the Tuck School of Business at Dartmouth College in the United States. Dr French together with Dr Eugene F. Fama developed the Fama French three-factor model and provide the factors through a data library the Dartmouth College website for the United States as well as for other international markets. The data library includes the factors for Asia Pacific excluding Japan which are applicable for Australia and hence are used in this study.

Calculating the Fama French factors based on Australian data would be preferable but is beyond the scope of this master's thesis. As a result, this study initially employs CAPM in the first instance to calculate abnormal return and compares results to the Fama French three-factor model for robustness.

3.3.3.1 CUMULATIVE ABNORMAL RETURN USING CAPM

Based on the CAPM, the firm beta coefficient is estimated for the 250 trading days prior to the observation period. Prior literature uses a pre-estimation window for the factor coefficients of 250 trading days (Luo et al., 2013; Tirunillai & Tellis, 2012) and hence this study applies this process.

$$R_{it} - R_{ft} = \alpha_i + \beta_{i_{MKT}} \left(R_{MKT_t} - R_{f_t} \right) + \varepsilon_{it} \qquad (3.1)$$

Where *i* denotes the firm and *t* for the time period, and

- R_{it} is the return of the firm *i* in time *t*,
- R_{ft} is the risk free rate of return ,
- R_{MKT} is the market portfolio return
- β is the factor coefficient

R_{it} is calculated as $R_{it} = PCl_{it}\text{-}POp_{it}$ *(3.2)*

Where *i* denotes the firm and *t* for the time period, and

- R_{it} is the return of the firm *i* in time *t*,
- PCl_{it} is the closing share price of firm *i* in time *t*,
- POp_{it} is the opening share price of firm *i* in time *t*,

Utilising the coefficient estimated in formula 3.1, the abnormal return for each firm based on CAPM is calculated as follows:

$$R_{Abit} = [R_{i_{t+1}} - R_{f,t+1}] - \{\hat{\beta}_{i_{MKT}} \left(R_{MKT_{t+1}} - R_{f_{t+1}} \right) \qquad (3.3)$$

Where:

- R_{Abit} – abnormal return of the firm *i* in time *t*,
- R_{it} denotes the stock return of firm *i* in time *t*, the daily closing price
- R_{ft} denotes the risk free rate of return based on a 12 month Australian Treasury Bill
- R_{MKT} denotes the market portfolio return for the ASX200 on day *t*
- $\hat{\beta}_i$ denotes the estimated factor coefficient for firm *i*

The cumulative abnormal return for the CAPM model for the first day is calculated as follows.

$$CAR\ CAPM_{it} = R_{Abi_{t-1}} + R_{Abit} \qquad (3.4)$$

Where *i* denotes the firm and *t* for the time period, and

- CAR_CAPM_{it} is the cumulative abnormal return of the firm *i* in time *t*
- R_{Abit} – abnormal return of the firm *i* in time *t*

For each subsequent day the cumulative abnormal return is calculated as follows:

$$CAR\ CAPM_{it} = CAR\ CAPM_{it_{t-1}} + R_{Abit} \qquad (3.5)$$

3.3.3.2 CUMULATIVE ABNORMAL RETURN USING FAMA -FRENCH THREE-FACTOR MODEL

The firm's coefficient for the three factors based on the Fama French three-factor model is estimated for the 250 trading day estimation window as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i_{MKT}}\left(R_{MKTt} - R_{f_t}\right) + \beta_{i_{SMB}} SMB_t + \hat{\beta}_{i_{HML}} HML_t + \varepsilon_{it} \qquad (3.6)$$

Where *i* denotes the firm and *t* for the time period, and

- R_{it} is the return of the firm *i* in time *t*
- R_{ft} is the risk free rate of return
- R_{MKT} is the market portfolio return
- *SMB* is the small minus big market capitalisation factor
- *HML* is the high minus low book to market factor
- βs are the factor coefficients

R_{it} is calculated as $R_{it} = PCl_{it}\text{-}POp_{it}$ *(3.7)*

Where *i* denotes the firm and *t* for the time period, and

- R_{it} is the return of the firm *i* in time *t*
- PCl_{it} is the closing share price of firm *i* in time *t*
- POp_{it} is the opening share price of firm *i* in time *t*

The coefficients estimated in formula 3.6 are then used to calculate the abnormal return for each firm based on the Fama French three-factor model as follows:

$$R_{AbFFit} = [R_{i_{t+1}} - R_{f_{t+1}}] - \{\hat{\beta}_{i_{MKT}}\left(R_{MKTt+1} - R_{f_{t+1}}\right) + \hat{\beta}_{i_{SMB}}SMB_{t+1} + \hat{\beta}_{i_{HML}}HML_{t+1} \qquad (3.8)$$

Where *i* denotes the firm and *t* for the time period, and

- R_{AbFFit} is the abnormal return of the firm *i* in time *t*
- R_{it} denotes the stock return of firm *i* in time *t*, the daily closing price
- R_{ft} denotes the risk free rate of return based on a 12 month Australian Treasury Bill
- R_{MKT} denotes the market portfolio return for the ASX200 on day *t*
- *SMB* is the small minus big market capitalisation factor

- *HML* is the high minus low book to market factor
- $\hat{\beta}_i$ denotes the estimated factor coefficients for firm *i*

The cumulative abnormal return for the Fama French three-factor model for the first day is calculated as follows.

$$CAR\ FF_{it} = R_{Abi_{t-1}} + R_{Abit} \tag{3.9}$$

Where i denotes the firm and t for the time period, and

- $CAR_{FFi,t}$ is the cumulative abnormal of the firm *i* in time *t*
- R_{Abit} is the abnormal return of the firm *i* in time *t*

For each subsequent day the cumulative abnormal return is calculated as follows:

$$CAR\ FF_{it} = CAR\ FF_{it_{t-1}} + R_{Abit} \tag{3.10}$$

3.3.4 Independent variables

The independent variables for this study represent the social media follower numbers for Facebook, LinkedIn and Twitter, the social media network presence size for each of those networks as well as the B2C variable. The variables *Facebook, LinkedIn* and *Twitter* are defined as the total follower numbers of the relevant social media profile or profiles for each individual firm divided by total assets. The variables *LargeSM, LargeFb, LargeLi* and *LargeTw* are defined as the social media presence size. *LargeSM* is coded one if the firm's total social media follower number across all three social media networks is above the median for the whole sample and zero otherwise. Similarly, the variables *LargeFb, LargeLi* and *LargeTw* are coded one if, on the respective social media network, the follower numbers for the firm were above the mean of the whole sample and zero otherwise. Finally, *B2C* is defined as the firm's business orientation based on the firm's global industry classification standard (GICS) grouping as being a member of the Consumer Discretionary, Consumer Staples or Industrial sector, and coded one if the firm has a B2C orientation and zero otherwise. Appendix A provides more details.

3.3.5 CONTROL VARIABLES

A number of control variables are relied on this study. These are firm characteristics and are *Earnings, Leverage, News* and *Size*. The *Earnings* variable controls for the impact of earnings on cumulative abnormal return and is defined as the return on assets. For this study the return on assets is calculated by Earnings before Interest and Taxes (EBIT) divided by the average total assets. The *Leverage* variable controls for the impact of leverage on cumulative abnormal return and is defined as total debt divided by total assets. The *News* variable controls for the impact of firm specific news on cumulative abnormal return and is coded one if on day *i* firm specific news was published, and zero otherwise. Lastly, the *Size* variable controls for the impact of firm size on cumulative abnormal return and is defined as the log of total assets.

Table 4 provides the definition of each variable used in the study. The cumulative abnormal return variables are the dependent variables while the social media network follower numbers, *Facebook, LinkedIn, Twitter, LargeSM, LargeFb, LargeLi* and *LargeTw* and *B2C* variables are the independent variables, the remainder comprise the control variables.

TABLE 4 – VARIABLES

Variable		Definition
CAR_CAPM	=	Cumulative Abnormal Return based on CAPM
CAR_FF	=	Cumulative Abnormal Return based on Fama French three-factor model
Facebook	=	Total number of Facebook page likes scaled by total assets
LinkedIn	=	Total number of LinkedIn page followers scaled by total assets
Twitter	=	Total number of Twitter page followers scaled by total assets
B2C	=	Coded 1 if a firm is a Business-to-Consumer firm based on global industry classification standard, and 0 otherwise
LargeSM	=	Coded 1 if a firm has an overall large presence on social media based on the median of the overall scaled social media network follower numbers, and 0 otherwise
LargeFb	=	Coded 1 if a firm has an overall large presence on Facebook based on the median of the Facebook follower numbers, and 0 otherwise
LargeLi	=	Coded 1 if a firm has an overall large presence on LinkedIn based on the median of the LinkedIn follower numbers, and 0 otherwise
LargeTw	=	Coded 1 if a firm has an overall large presence on Twitter based on the median of the Twitter follower numbers, and 0 otherwise
Earnings	=	Return on assets, measured as EBIT/Average total assets
Leverage	=	Debt to assets
News	=	Coded 1 if a firm had firm specific news on day *i*, and 0 otherwise
Size	=	Log of total assets in t_0

3.4 DATA ANALYSES

This study uses several statistical techniques to test the hypotheses outlined in Chapter 2. This section outlines the statistical methods employed to test the relationship between social media network activity and corporate value based on the social media value (SMV) model. It commences with a discussion on analysis of variance, continues with a discussion on regression and factor analysis and concludes with the model specification.

Panel data methods are selected as the main estimation technique for this study. Based on the nature of the relationship under investigation, panel data offer a range of advantages, including the ability to test the SMV model cross-sectionally as well as periodically over time. The method affords the opportunity to test (*n*) number of firms over a time period (*t*) of 30 days. The cross sectional analysis enables testing of the hypotheses proposed for this study at a certain point in time while the time-series aspect allows for the establishment of correlations over time.

3.4.1 ANALYSIS OF VARIANCE

Analysis of variance (ANOVA) is used to determine whether there is a relationship between social media network activity and corporate value. This statistical method is used to examine the difference of the variances between two or more groups. The method is appropriate when studying the effect of a categorical variable on a continuous (metric) variable (Iversen & Norpoth, 1987). An ANOVA test is the test to identify factors that influence a given outcome; it is used to test general rather than differences among means. It is accepted that the method lacks the capability to provide in depth insights into the relationship, yet is considered useful to provide a fundamental insight.

When the number of factors under consideration is more than one, the test is referred to as N-Way Analysis of Variance. The 3-Way Analysis of Variance is being considered in this study. The 3-Way Analysis of Variance is a statistical test used to determine the effect of three nominal predictor variables on a continuous outcome variable. A three-way ANOVA test analyses the effect of the independent variables on the expected outcome along with their relationship to the outcome itself.

The sample for this study consists of observations made examining three different social media platforms namely Facebook, LinkedIn and Twitter. A dichotomous variable is coded one if a firm maintains a large presence on the relevant social media network as well as for the combined social media networks and zero otherwise. Hence two groups for each social media network as well as overall social media presence are observed on the outcome variable, cumulative abnormal return, which is measured on the continuous scale. A further dichotomous variable is created which is coded one of the firm is a B2C firm and zero otherwise.

3.4.2 REGRESSION

Panel data regression models can be separated into three main model types, mixed ordinary least squares (MOLS) models, fixed effect models (FEM) and random effect models (REM) (Gujarati, 2009). Mixed OLS regression, fixed and random effects models as well as autoregressive regression are used to investigate whether more specific insights can be obtained from the data and to test the robustness of the analysis. The following subsections expand on each of those models in generic terms and the specific terms are outlined in section 3.5.

3.4.2.1 MIXED OLS

The mixed OLS model is the simplest panel data approach and stacks all observations for each firm on top of each other and estimates a standard OLS regression as seen in the example below:

$$Y_{it} = \beta_1 + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it} \tag{3.11}$$

A mixed OLS regression in the present study would suggest that all firms display the same characteristics, implying that there are no unobserved differences present. This follows the same logic as standard OLS and assumes that errors are independent and identically distributed, $u_{it} \sim iid\ (0, \sigma_u^2)$. A key challenge with mixed OLS is that its assumptions are overly simplistic and unrealistic (Gujarati, 2009). For example assuming that slope coefficients of the X variables are identical is unrealistic as it assumes that firm size and share value growth is identical across all firms. Furthermore, should unobserved heterogeneity exist within the model, OLS estimators will be biased due to correlation of the error term with the X variables. Therefore, due to the high likelihood of heterogeneity mixed OLS would only have limited suitability in this study, as it would likely distort the true nature of the relationship between the Y and X variables across all the sampled firms.

3.4.2.2 FIXED EFFECTS MODELS (FEM)

The fixed effects model allows the consideration of the individuality of each cross sectional unit or in the case of this study, each firm. This is captured by the intercept term having an *i* subscript indicating that there may be heterogeneity across all 74 companies. Gujarati (2004) explains that the term "fixed–effects" arises because although the intercepts may vary across cross sectional units they remain constant or fixed over time.

$$Y_{it} = \beta_{1i} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it} \tag{3.12}$$

3.4.2.3 RANDOM EFFECTS MODELS (REM)

Random-effects models (REM) represent an alternative to fixed effect models, where REM expresses the lack of knowledge on the true model through the disturbance term as opposed to through the intercept (Gujarati, 2004). Therefore, the REM investigates differences in the variance of error terms in the hope that an inference can be made on the general population based on these differences.

Revisiting Equation 3.12 from the FEM, the intercept term β_{1i} is not treated as a fixed term but rather thought of as a random variable with a mean of β_1. Therefore, the intercept value is written as follows:

$$\beta_{1i} = \beta_1 + \varepsilon_i \quad i = 1, 2, \dots, N \tag{3.13}$$

Where ε_i is a random error term that is independent and identically distributed, $\varepsilon_i \sim iid\ (0, \sigma_u^2)$. This model assumes that all firms in the present study are drawn from a larger universe of similar firms with a common intercept value whilst the individual heterogeneity of each firm's intercept is displayed in the error term, ε_1.

Substituting Equation 3.13 into Equation 3.12 derives Equation 3.14 as follows:

$$Y_{it} = \beta_1 + \beta_2 X_{2it} + \beta_3 X_{3it} + \omega_{it} \tag{3.14}$$

$$\omega_{it} = u_{it} + \varepsilon_i \tag{3.15}$$

Equation 3.14 now has a composite error term, which is made up of two components that include ε_1 or the firm specific error component and u_{it}, which is the combined time–series and cross section error component (Gujarati, 2004). The firm specific error component ε_1 is not readily observable and is thus known as the unobserved heterogeneity within the model. The REM employs the usual assumptions of no correlation amongst firm error components and the lack of autocorrelation amongst time–series and cross sectional units.

3.4.3 Factor analysis

Factor analysis is used to determine whether the social media variables used in this study represent a latent variable (Kim & Mueller, 1978). Given all three independent variables represent social media networks it is possible that those variables represent an underlying variable. It is expected that Facebook and Twitter are more similar than either of the two networks and LinkedIn. This is due to the fact that both Facebook and Twitter focus on the broader population while LinkedIn focuses on professionals only. Factor analysis condenses variables by exploring underlying factors. Thus the factors provide an insight into underlying patterns as well as highlight how the individual social media network follower numbers load on each established factor. Through factor analysis a better understanding of the differences between the social media networks can be achieved. This study employs exploratory principal component factor analysis with varimax rotation.

3.5 Model specification

The multivariate analysis in this study is undertaken using Stata econometric software. Specifically, ordinary least squares (OLS) methods are used to estimate the study model and expanded upon using a fixed effects model. These methods are not unique to this study and have been employed in prior research (Du & Jiang, 2015; Paniagua & Sapena, 2014). Similarly Tirunillai and Tellis (2012) and Luo et al. (2013) have also tested the relationship between social media measures and corporate value using Vector Autoregressive models. The SMV model defined in Chapter two expands on the model used by Paniagua and Sapena (2014) to include LinkedIn as an additional social media network. This study also expands the corporate value measurements. In this study corporate value is measured in two ways, abnormal return based on the CAPM model and abnormal return based on the Fama French three-factor model.

Regressing the social media network follower numbers on the abnormal return is the final step to test hypothesis one. The model empirically estimated in this study is constructed as follows:

$$CAR\_CAPM_{it} = \beta_0 + \beta_1 Facebook_{it} + \beta_2 LinkedIn_{it} + \beta_3 Twitter_{it} + \beta_4 B2C_{it} + \beta_5 Earnings_{it} + \beta_6 Leverage_{it} + \beta_7 News_{it} + \beta_8 Size_{it} + \gamma_i + \lambda_t + \varepsilon_t \quad (3.16)$$

Where *i* denotes an Australian firm listed on the Australian Stock Exchange, *t* denotes time (daily) and the following variables are used:

- CAR_CAPM_{it} – cumulative abnormal return based on CAPM for firm *i* on day *t*
- *Facebook* – daily Facebook likes, measured as the total likes for firm *i* scaled by total assets on day *t*
- *Twitter* – daily Twitter followers, measured as the total followers for firm *i* scaled by total assets on day *t*
- *LinkedIn* – daily LinkedIn followers, measured as the total followers for firm *i* scaled by total assets on day *t*
- *B2C* – firm specific B2C dummy variable for firm *i* on day *t*, 1 if firm is consumer focused, 0 otherwise
- *Earnings* – return on assets, measured as EBIT divided by average total assets for firm *i* on day *t*
- *Leverage* – debt to assets, measured as total debt divided by total assets for firm *i* on day *t*
- *News* – firm specific events dummy variable for firm *i* on day *t*, 1 if firm specific event, 0 otherwise
- *Size* – measured as log of total assets for firm *i* on day *t*
- γ – firm fixed effects dummy variable
- λ – time fixed effects dummy variable
- ε – error term

To test hypothesis two the additional interaction terms of *B2C* and each of the social media networks is included in the model. The model below is an extension on equation 3.16.

$$CAR\_CAPM_{it} = \beta_0 + \beta_1 Facebook_{it} + \beta_2 LinkedIn_{it} + \beta_3 Twitter_{it} + \beta_4 Facebook_{it}\#B2C_{it} + \beta_5 LinkedIn_{it}\#B2C_{it} + \beta_6 Twitter_{it}\#B2C_{it} + \beta_7 B2C_{it} + \beta_8 Earnings_{it} + \beta_9 Leverage_{it} + \beta_{10} News_{it} + \beta_{11} Size_{it} + \gamma_i + \lambda_t + \varepsilon_t \quad (3.17)$$

Where all variables are identical to equation 3.16 and additionally the squared terms are added as follows:

- *Facebook#B2C* – the interaction term for *Facebook* and *B2C* for firm *i* on day *t*
- *LinkedIn#B2C* – the interaction term for *LinkedIn* and *B2C* for firm *i* on day *t*
- *Twitter#B2C* – the interaction term for *Twitter* and *B2C* for firm *i* on day *t*

The calculation of the coefficients for the social media network follower numbers and the squared term of the social media network follower numbers with the dependent variable being cumulative abnormal return is required to test hypothesis three.

$$CAR\_CAPM_{it} = \beta_0 + \beta_1 Facebook_{it} + \beta_2 Facebook^2_{it} + \beta_3 LinkedIn_{it} + \beta_4 LinkedIn^2_{it} + \beta_5 Twitter_{it} + \beta_6 Twitter^2_{it} + \beta_7 B2C_{it} + \beta_8 Earnings_{it} + \beta_9 Leverage_{it} + \beta_{10} News_{it} + \beta_{11} Size_{it} + \gamma_i + \lambda_t + \varepsilon_t \quad (3.18)$$

Where all variables are identical to equation 3.13 and additionally the squared terms are added as follows:

- *Facebook*^{2} – the squared term of daily Facebook 'likes', measured as the total likes for firm *i* scaled by total assets on day *t*
- *Twitter*^{2} – the squared term of daily Twitter followers, measured as the total followers for firm' scaled by total assets on day *t*
- *LinkedIn*^{2} – the squared term of daily LinkedIn followers, measured as the total followers for firm' scaled by total assets on day *t*

To establish the critical values for each of the social media networks, the following formulae are used:

$$Facebook_{Cr} = \frac{\hat{\beta}_1}{2\hat{\beta}_2} \qquad (3.19)$$

$$Twitter_{Cr} = \frac{\hat{\beta}_3}{2\hat{\beta}_4} \qquad (3.20)$$

$$LinkedIn_{Cr} = \frac{\hat{\beta}_5}{2\hat{\beta}_6} \qquad (3.21)$$

Where FB_{Cr} = Facebook critical values; TW_{Cr} = Twitter critical values and LI_{Cr} = LinkedIn critical values.

3.5.1 TESTS

3.5.1.1 HETEROSKEDASTICITY

One assumption of the OLS model is that the variables are homoscedastic, the dependent variable has a similar amount of variance across the values for an independent variable. Due to the nature of the underlying data and based on prior literature it is anticipated that this assumption might be violated. To detect heteroscedasticity this study employs the Wald test and should heteroscedasticity be present uses the Huber / White correction to address this challenge.

3.5.1.2 HAUSMAN TEST

The Hausman test is used to decide between the choice of FEM and REM as it tests whether individual effects are uncorrelated with other variables in the regression. The null hypothesis of the Hausman test is that the FEM and REM estimators are essentially the same. The test statistic has an asymptotic χ^2 distribution. Hence, it follows that rejection of the null hypothesis indicates that the REM is not suitable and the FEM is more appropriate.

3.5.1.3 AUTOCORRELATION

Due to the time series characteristic of panel data it is possible that autocorrelation exists in the data set. To detect autocorrelation in the sample, the Wooldridge test is utilized. Should autocorrelation be present in the data set, an autoregressive model is employed similar to the models used by Tirunillai and Tellis (2012) and Luo et al. (2013).

3.5.1.4 Unit root / stationarity tests

The phenomenon of spurious regression might be present in this study due to the time dimension of the panel sample (Granger and Newbold, 1974). Results of a regression are spurious if the time dimension of the variable is non-stationary. Non-stationarity is potentially an issue for panels with *t* -> infinity. Hence non-stationarity is not likely in this study due to the short observation window. However, for completeness a unit root test (Choi, 2001) with the null hypothesis that non-stationarity is present in all series is applied to test for non-stationarity. A significant test result would reject the null hypothesis and indicates a stationary variable.

3.5.1.5 Multicollinearity

The absence of multicollinearity is another assumption in an OLS model and considering the three independent variables are all extracted from social media networks, multicollinearity is potentially present in this study. A test for Variance Inflation factors (VIF) is used to test for multicollinearity.

3.6 Chapter conclusion

This chapter set out the methods applied to examine the relationship between social media network activity and corporate value. The components outlined are the sample selection, a description of the data used for this study as well as a section on data analysis. For the data analysis the chapter continues with an outline of the statistical methods used in this study, ANOVA, regression and factor analysis. The chapter concludes with the model specifications to test the hypotheses and a discussion about relevant tests.

In the following chapter the findings of the study are outlined, including the descriptive statistics, the analyses to test the hypotheses, a comparison of results using CAPM and Fama French three-factor model as well as assumption and robustness testing.

Chapter 4. RESULTS

4.1 INTRODUCTION

This chapter reports the results for the empirical analysis performed based on chapter three to test the hypotheses developed in chapter two. The chapter commences with a reconciliation of daily share trading data to the observation period and descriptive statistics. The next sections outline the results for each of the four hypotheses, followed by comparison of results between CAPM and Fama French three-factor model, assumption testing as well as robustness tests.

4.2 SHARE TRADING DAILY DATA FOR ANALYSIS

The observation period covers the thirty days in the month of June 2016. Of those 30 days, ten days are excluded due to being non-trading days (weekends and public holidays) and a further two days are excluded because of the method of calculating cumulative average return. Thus, 18 days of observations are included in the study. Table 5 presents the reconciliation from the total observation period to the number of days' share trading included in the analysis.

TABLE 5 – SHARE TRADING OBSERVATION PERIOD RECONCILIATION

Description	Number of Days
Total observation window	30
Non-trading days (weekends and public holidays)	(10)
Days required to calculate abnormal return	(2)
Net days available for analysis	18

Two firms in the sample have incomplete trading data due to no share volume on certain days. The stock of Austral Ltd was not traded on the day of 30th June 2016 translating into no *CAR* observation for the 29th June 2016. Similarly, Pacific Brands Ltd's stock was not traded on the two days of 29th and 30th June 2016, translating into a further two observations for *CAR* not being available. Accordingly, the number of observations for which *CAR* is calculated is 1,329, as denoted in Table 6.

TABLE 6 – NUMBER OF OBSERVATIONS

Description	Number of Observations
74 firms x 18 days	1,332
Days firm data not available due to no trading volume	3
Number of observations for the study	1,329

4.3 SOCIAL MEDIA NETWORK FOLLOWER DATA

Chapter 3 described the social media network follower numbers of the sampled firms. Daily social media network follower number data for the month of June 2016 were downloaded for each firm from socialreport.com. It is noted that for days where no changes in social media network follower numbers occurred, the last recorded follower number was collected.

Descriptive statistics for social media network follower data by each network are presented in Table 7

TABLE 7 – DESCRIPTIVE STATISTICS SOCIAL MEDIA NETWORK FOLLOWING DATA

Network	Mean	St Dev	Min	Max
Facebook	124556.2	364988.3	0	2447078
LinkedIn	13629.1	24351.4	0	193207
Twitter	24521.0	97743.8	0	667937
The above data are unscaled. *n* = 1,329.				

The table above describes the raw social media network follower numbers for the firm profiles extracted for the study. The large follower numbers in terms of mean, standard deviation as well as the range of follower numbers for Facebook reflect the significantly larger user numbers of this social media network. As outlined in Figure 1, Chapter 1, the global user numbers for Facebook are significantly larger than those for LinkedIn and Twitter globally and as discussed in section 1.1 this is equally the case for Australia. LinkedIn, while widely used within the sample firms, does not have the large follower numbers Twitter has. This seems to be sensible as Twitter is a more consumer focused network than LinkedIn and the large representation of B2C firms in the sample magnifies that effect.

Table 8 shows the categorisation of the 74 sample firms as B2B or B2C depending on the focus of the firm. Some 21firms (28.4% of sample) belong to the industrial sector and have been categorised as B2B. The remaining 53 firms (71.6%) are in the consumer discretionary and consumer staples sectors and are categorised here as B2C.

TABLE 8 – SAMPLE CATEGORISATION AS B2B AND B2C

Description	*n*	%
Business-to-Business	21	28.4%
Business-to-Consumer	53	71.6%
	74	100.0%

The sample is further broken by the number of social media networks to which the firms in each category belong. Table 9 provides a summary.

TABLE 9 – SOCIAL MEDIA NETWORK PRESENCE CLASSIFIED BY FIRM FOCUS (B2B, B2C)

# of Networks	B2B	%	B2C	%	Total	%
0	2	9.5%	1	1.9%	3	4.1%
1	5	23.8%	11	20.8%	16	21.6%
2	7	33.3%	17	32.1%	24	32.4%
3	7	33.3%	24	45.3%	31	41.9%
	21		53		74	

Taking the sample as a whole, 31 firms (41.9%) maintain a presence on all three social media networks. Those firms with a presence on two social media networks number 24 (32.4%), while 16 (21.6%) firms have one social media network presence, and three (4.1%) are not represented on any of the three social media networks.

The firms categorised as B2B maintain social media profiles across all three social media networks with seven (33.3%) maintaining a profile on each social media network, a further seven (33.3%) maintaining a profile on two of the social media networks and five firms (23.8%) maintaining one social media profile. Only two firms or 9.5% of all B2B firms maintain no profile on any of the three social media networks.

Firms in the B2C category maintain higher social media profiles across all three social media networks. Some 24 (45.3%) firms maintain a profile on each social media network, 17 (32.1%) have profiles on two of the social media networks and 11 (20.8%) firms maintain one social media profile. Only one firm or 1.9% of all B2C firms has no representation on any of the social media networks included in this study. It is intuitively sound that firms that focus their business transactions directly with consumers are likely to have a greater presence on social media networks. Thus the results of Table 9 are not unexpected.

4.4 SAMPLE DESCRIPTIVE STATISTICS

Table 10 reports th**e** descriptive statistics for the total sample. Two alternate calculations for the dependent variable, cumulative abnormal return, estimated as described in Chapter 3, are reported. The cumulative abnormal return based on CAPM (*CAR_CAPM)* range from -0.154 to 0.108, with a mean of -0.004 and a standard deviation of 0.030. The cumulative abnormal return based on the Fama French three-factor model (*CAR_FF)* range from -0.120 to 0.111 with a mean of 0.001 and a standard deviation of 0.024.

The three independent variables *Facebook*, *LinkedIn* and *Twitter* are scaled by total assets and as indicated in Table 7, social media follower numbers range significantly across the networks. Facebook (*Facebook*) has a mean of 56.651 (minimum 0, maximum 902.740, standard deviation 171.056), while the mean for LinkedIn (*LinkedIn*) is 6.370 (minimum 0, maximum 52.070, standard deviation 8.315), and Twitter (*Twitter*) has a mean of 9.614 (minimum 0, maximum 333.179, standard deviation 39.067). The final independent variable *B2C* is a dichotomous variable, and the mean of 0.716 indicates that 71.6% of firms are B2C firms.

The four control variables *Earnings*, *Leverage*, *News* and *Size* as described Table 4 are presented with their relevant descriptive statistics. Return on Assets (*Earnings*) has a mean of 0.097 reflecting on a mean return on assets of 9.7% (minimum -0.115, maximum 0.408, standard deviation 0.07). Debt to assets (*Leverage*) has a mean of 0.485 translating in a mean funding of 48.5% of total assets through debt (minimum 0.032, maximum 0.91, standard deviation 0.152). News (*News*) is a dichotomous variable, and the mean of 0.874 indicates that firms have firm-specific news on 87.4% of observation days. This is to be expected as the sample is drawn from the largest listed firms in Australia and it could be assumed that those firms attract regular news coverage. The final control variable is Size (*Size*) which is the log transformed total asset number for each firm and has a mean of 7.541 (minimum 5.913, maximum 10.616, standard deviation 1.078).

TABLE 10 – DESCRIPTIVE STATISTICS – TOTAL SAMPLE

Variable	n	Mean	Std.Dev.	Min	Max
CAR_CAPM	1329	-0.004	0.030	-0.154	0.108
CAR_FF	1329	0.001	0.024	-0.120	0.111
Facebook	1329	56.651	171.056	0	902.740
LinkedIn	1329	6.370	8.315	0	52.070
Twitter	1329	9.614	39.067	0	333.179
B2C	1329	0.716	n/a	n/a	n/a
Earnings	1329	0.097	0.070	-0.115	0.408
Leverage	1329	0.485	0.152	0.032	0.910
News	1329	0.874	n/a	n/a	n/a
Size	1329	7.541	1.078	5.913	10.616

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CAR_FF* = Cumulative Abnormal Return based on Fama French three-factor model, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *B2C* = Coded 1 if a firm is a Business-to-Consumer firm based on global industry classification standards, and 0 otherwise, *Earnings* = Return on assets, *Leverage* = Debt to assets, *News* = Coded 1 if a firm had firm specific news report, and 0 otherwise, *Size* = Log of total assets.

Some 21 firms (28.4% of total sample) are in the B2B category. Table 11 reports the descriptive statistics for this subsample. The cumulative abnormal return based on CAPM (*CAR_CAPM)* range from -0.095 to 0.108, with a mean of -0.003 and a standard deviation of 0.030. The cumulative abnormal return based on the Fama French three-factor model (*CAR_FF)* range from -0.076 to 0.075 with a mean of 0.000 and a standard deviation of 0.025.

Facebook (*Facebook*) has a mean of 4.634 (minimum 0, maximum 93.521, standard deviation 19.836), while the mean for LinkedIn (*LinkedIn*) is 7.136 (minimum 0, maximum 52.070, standard deviation 11.855), and Twitter (*Twitter*) has a mean of 0.967 (minimum 0, maximum 13.886, standard deviation 2.925). The subset shows a higher mean and standard deviation for LinkedIn while the means and standard deviations for Facebook and Twitter are lower in comparison to the full sample. This emphasises LinkedIn for B2B firms given the fact that most firms maintain a LinkedIn profile but to a lesser extent profiles on the other social media networks.

Return on assets (*Earnings*) has a mean of 0.071 reflecting on a mean return on assets of 7.1% (minimum -0.115, maximum 0.207, standard deviation 0.068). Debt to assets (*Leverage*) has a mean of 0.497 indicating average funding of 49.7% of total assets through debt (minimum 0.032, maximum 0.910, standard deviation 0.172). News (*News*) is a dichotomous variable, and the mean of 0.878 indicates that firms have firm specific news on 87.8% of observation days. The final control variable is Size (*Size*) which is the log transformed total asset number for each firm and has a mean of 7.791 (minimum 5.982, maximum 10.044, standard deviation 1.191).

TABLE 11 – DESCRIPTIVE STATISTICS – B2B FIRMS

Variable	n	Mean	Std.Dev.	Min	Max
CAR_CAPM	377	-0.003	0.030	-0.095	0.108
CAR_FF	377	0.000	0.025	-0.076	0.075
Facebook	377	4.634	19.836	0	93.521
LinkedIn	377	7.136	11.855	0	52.070
Twitter	377	0.967	2.925	0	13.886
Earnings	377	0.071	0.068	-0.115	0.207
Leverage	377	0.497	0.172	0.032	0.910
News	377	0.878	n/a	n/a	n/a
Size	377	7.791	1.191	5.982	10.044

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CAR_FF* = Cumulative Abnormal Return based on Fama French three-factor model, *Facebook* = Total number of Facebook page ‘likes’ scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *Earnings* = Return on assets, *Leverage* = Debt to assets, *News* = Coded 1 if a firm had firm specific news report, and 0 otherwise, *Size* = Log of total assets.

B2C firms represent 53 (71.6%) of the total 74 firms in this study. The descriptive statistics for this subsample are reported in Table 12. The cumulative abnormal return based on CAPM (CAR_CAPM) range from -0.154 to 0.100, with a mean of -0.005 and a standard deviation of 0.030. The cumulative abnormal return based on the Fama-French three-factor model (CAR_FF) range from -0.120 to 0.111 with a mean of 0.001 and a standard deviation of 0.0232.

Facebook (*Facebook*) has a mean of 77.250 (minimum 0, maximum 902.740, standard deviation 198.007), while the mean for LinkedIn (*LinkedIn*) is 6.067 (minimum 0, maximum 29.800, standard deviation 6.377), and Twitter (*Twitter*) has a mean of 13.038 (minimum 0, maximum 333.179, standard deviation 45.679). This subset shows higher means and standard deviations for Facebook and Twitter while the mean and standard deviation for LinkedIn is slightly lower in comparison to the full sample. This emphasises LinkedIn for B2C firms given the fact that most firms maintain a LinkedIn profile but to a lesser extent profiles on the other social media networks. This emphasises Facebook and Twitter for B2C firms which is expected, given the more consumer focus of those firms.

The data for the control variables limited to B2C firms are summarised as follows. Return on assets (*Earnings*) has a minimum of -3.2% and a maximum of 40.8% with a mean of 10.7% (standard deviation 6.9%). Debt to assets (*Leverage*) has a minimum of 0.170 and a maximum of 0.824 indicating a range of 17% to 82.4% of total assets are funded through debt, and the mean is 0.481 (standard deviation 0.142). News (*News*) indicates that firms have firm specific news on 87.3% of observation days. The final control variable is Size (*Size*) which is the log transformed total asset number for each firm and has a minimum of 5.913 and a maximum of 10.616, and a mean of 7.443, (standard deviation 1.013).

TABLE 12 – DESCRIPTIVE STATISTICS – B2C FIRMS

Variable	n	Mean	Std.Dev.	Min	Max
CAR_CAPM	952	-0.005	0.030	-0.154	0.100
CAR_FF	952	0.001	0.232	-0.120	0.111
Facebook	952	77.250	198.007	0	902.740
LinkedIn	952	6.067	6.377	0	29.800
Twitter	952	13.038	45.679	0	333.179
Earnings	952	0.107	0.069	-0.032	0.408
Leverage	952	0.481	0.142	0.170	0.824
News	952	0.873	n/a	n/a	n/a
Size	952	7.443	1.013	5.913	10.616

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CAR_FF* = Cumulative Abnormal Return based on Fama French three-factor model, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *Earnings* = Return on assets, *Leverage* = Debt to assets, *News* = Coded 1 if a firm had firm specific news report, and 0 otherwise, *Size* = Log of total assets.

Table 13, below, shows the correlation matrix between the key variables in the study. With the exception of the correlation between *Size* and *Earnings*, all variables in the study show a weak correlation. *Size* and *Earnings* show a moderate negative but significant correlation of -0.318 ($p<0.01$). The *News* variable has a significant correlation *Leverage* only (0.103, $p<0.01$).

TABLE 13 – CORRELATION MATRIX

	Facebook	*LinkedIn*	*Twitter*	*B2C*	*Earnings*	*Leverage*	*News*	*Size*
Facebook	1.000							
LinkedIn	0.219 ***	1.000						
Twitter	0.067 **	-0.018	1.000					
B2C	0.191 ***	-0.058 **	0.139 ***	1.000				
Earnings	0.158 ***	0.085 ***	0.059 **	0.234 ***	1.000			
Leverage	0.130 ***	0.057 **	-0.065 ***	-0.049 *	0.101 ***	1.000		
News	-0.010	0.014	-0.016	-0.007	-0.024	0.103 ***	1.000	
Size	-0.148 ***	-0.251 ***	-0.015	-0.015 ***	-0.318 ***	0.202 ***	0.223 ***	1.000

*** p<0.01, ** p<0.05, * p<0.1

Facebook = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *B2C* = Coded 1 if a firm is a Business-to-Consumer firm based on global industry classification standard, and 0 otherwise, *Earnings* = Return on assets, *Leverage* = Debt to assets, *News* = Coded 1 if a firm had firm specific news report, and 0 otherwise, *Size* = Log of total assets.

4.5 SOCIAL MEDIA NETWORK FOLLOWERS IMPACT ON CORPORATE VALUE

This sections provides for the results relevant for hypothesis one including relevant tests. Hypothesis one is developed in section 2.2.7 and states:

H1: The social media network follower numbers on Facebook, LinkedIn and Twitter impact the share return of firms.

To establish whether there is a statistically significant difference between a firm's social media network follower size, a new dichotomous variable (*LargeSM*) is created which splits the sample data into large social media network follower size firms (1) and small social media network follower size firms (0). To determine a total follower size, the social media network follower numbers are summed and split at the median, with firms with social media network follower numbers above the median being classified as large social media network follower size firms, while those falling below the median being classified as small social media network follower size firms. An ANOVA is run to establish whether there is a significant difference between the two groups. Table 14, below, indicates a statistically significant difference between the two groups suggesting an underlying relationship between social media network follower numbers and cumulative abnormal return.

TABLE 14 – RESULTS FOR ONE-WAY ANOVA

Variable	***CAR_CAPM***	**Standard error**
LargeSM	-0.004**	-0.002
Observations	1,329	
R-squared	0.005	

*** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *LargeSM* = Coded 1 if a firm has an overall large social media presence, and 0 otherwise.

The table provides the results for the one-way ANOVA, analyzing mean differences between the two groups, firms with an overall large social media network follower size and those without an overall large social media network follower size. *LargeSM* is significant at a *p*-value of 0.05.

One of the assumptions of an ANOVA is normality which is violated as identified in a post hoc normality test (see table 15 below). Hence the results might be incorrect or misleading. Because of the violation of the normality assumption identified in a post hoc normality test (refer to Table 15 below), the Kruskal-Wallis equality-of-population rank test is performed and the results displayed in Table 16.

TABLE 15 – SHAPIRO-WILK TEST FOR NORMAL DATA

Variable	Obs	W	V	z	Prob>z
CAR (CAPM)	1,329	0.974	21.292	7.66	0.000
CAR_CAPM = Cumulative Abnormal Return based on CAPM					

The above table shows the test results for the Shapiro-Wilk test for normal data. The null for this test is that the data are normally distributed and for the data of this study the null is rejected at the 5% level. Further examinations of the normality assumptions such as a visual assessment and alternative tests such as Jarque-Bera (untabulated) confirm the above result.

TABLE 16 – KRUSKAL-WALLIS EQUALITY-OF-POPULATIONS RANK TEST

LargeSM	**Obs**	**Rank Sum**
0	665	451997.5
1	664	431787.5
chi-squared =	1.952 with 1 d.f.	
probability =	0.162	
chi-squared with ties =	1.952 with 1 d.f.	
probability =	0.162	
CAR_CAPM = Cumulative Abnormal Return based on CAPM, *LargeSM* = Coded 1 if a firm has an overall large social media presence, and 0 otherwise.		

Table 16 provides the results for Kruskal-Wallis equality-of-populations rank test for *LargeSM* on *CAR_CAPM*. The results show a significance level, which is 0.162 for the factor *LargeSM*. It is observed that the *p*-value for large social sedia presence is larger than the 5% level. Based on these results, we do not reject the null hypothesis and conclude that there is no significant difference between the effects of the size of firm presence on social media networks on the firm's abnormal return. That is, whether the firm maintains an overall large follower numbers on social media networks or not, does not differ in relation to the firm's abnormal return.

This results is somewhat surprising as prior literature indicates social media measures to impact corporate value. It is possible that the combination of the three social media network follower numbers masks individual relationships. Hence three individual Kruskal-Wall rank tests are performed with each focusing on one of the three social media networks follower size.Table 17 presents the results.

TABLE 17 –KRUSKAL-WALLIS EQUALITY-OF-POPULATIONS RANK TEST BY SOCIAL MEDIA NETWORK

	LargeFb		***LargeLi***		***LargeTw***	
	Large	**Small**	**Large**	**Small**	**Large**	**Small**
Observations	647	682	664	665	664	665
Rank Sum	418,069	465,717	428,333	455,452	422,097	461,689
chi-squared	3.037 with 1 d.f.		3.575 with 1 d.f.		7.741 with 1 d.f.	
probability	0.081		0.059		0.005	

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *LargeFb* = Coded 1 if a firm has a large Facebook presence, and 0 otherwise, *LargeLi* = Coded 1 if a firm has a large LinkedIn presence, and 0 otherwise, *LargeTw* = Coded 1 if a firm has a large Twitter presence, and 0 otherwise.

Table 17 provides the results for the Kruskal-Wallis equality-of-populations rank tests for *LargeFb*, *LargeLi* and *LargeTw* on *CAR_CAPM*. Each of the tests performed analyses whether a statistically significant difference exists between the independent variables, *Facebook*, *LinkedIn* and *Twitter* presence size on the continous dependent variable being cumulative abnormal return. The significance levels for each individual test are 0.081, 0.059 and 0.005 respectively for the independent variables Facebook presence size, LinkedIn presence size and Twitter presence size. Considering the 5% level, it is observed that the *p*-value for both Facebook and LinkedIn presence is larger than 0.05 while the *p*-value for Twitter is less than 0.05. However, both the Facebook and LinkedIn presence are marginally significant at the 10% level of significance.

Thus we do not reject the null hypothesis for both the Facebook and LinkedIn presence size at the 5% level and can conclude that there is no significant difference on the presence size of the firm on those two social media networks on the dependent variable. That is, the outcome of the variable *CAR* is not different between firms which have a large presence on Facebook or LinkedIn and firms that do not. Further, the null hypothesis for Twitter presence is rejected, and the conclusion is drawn that there is a significant difference of the Twitter presence size of the firm on the dependent variable. That is the outcome of the variable cumulative abnormal return is different between firms which have a large presence on Twitter and firms that do not.

A two way and three way ANOVA can be used to detect interactions between the independent variables. However, since the normality assumption is violated and to the knowledge of the author no non-prametric version of a three way ANOVA exists, examining the interaction between the three independent variables is challenging.

Given the statistically significant difference for the Twitter social media network presence size and the marginally significant difference for Facebook and LinkedIn, the fixed effect autoregressive regression is used to further explore the impact of social media network follower numbers on cumulative abnormal return. The use of the autoregressive regression is due to autocorrelation being detected when applying the Wooldridge test. The results are depicted below in Table 18.

TABLE 18 – WOOLDRIDGE TEST FOR AUTOCORRELATION IN PANEL DATA

H0: no first order autocorrelation	
F(1,73)	= 140.989
Prob>F	= 0.000

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets.

Table 18 provides the results for the Wooldridge test for autocorrelation in panel data for *Facebook*, *LinkedIn* and *Twitter* on *CAR_CAPM*. Considering the 5% level of significance, it is observed that the *p*-values for the test are less than 0.05. Thus we reject the null hypothesis and conclude that there is first order autocorrelation in the idiosyncratic error term in a panel-data model. To address the autorcorrelation in the model, an autoregressive regression is performed with the results shown in Table 19.

TABLE 19 – AUTOREGRESSIVE FIXED EFFECT MODEL

VARIABLES	*CAR_CAPM*	*Standard error*
Facebook	-0.001	0.001
LinkedIn	-0.049	0.036
Twitter	-0.002	0.009
Earnings	-0.324	0.968
Leverage	-0.664	1.321
News	-0.000	0.002
Constant	0.722**	0.335
Observations	1,255	
Number of firms	74	

*** p<0.01, ** p<0.05, * p<0.1.

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *Earnings* = Return on assets, *Leverage* = Debt to total assets, *News* = Coded 1 if a firm had firm specific news report, and 0 otherwise.

Table 19 provides the results for the autoregressive fixed effects model, analysing the impact of the variables of interest on *CAR_CAPM*. Given none of the independent variables *Facebook*, *LinkedIn* or *Twitter* are significant at the 5% level, we do not reject the null hypothesis and conclude that there is no significant correlation between the independent variables and the dependent variable. That is, the outcome of the cumulative abnormal return variable is not correlated with Facebook, LinkedIn or Twitter follower numbers.

In this section the impact of social media network activity and corporate value is examined. A statistically significant difference for Twitter presence and a marginally statistically significant difference for Facebook and LinkedIn are detected. However, no significant impact of the social media network follower numbers on cumulative abnormal return has been detected in the data.

4.6 INDUSTRY DIFFERENCE (B2B VS B2C)

Hypothesis two as shown below posits that a difference between Business-to-Business and Business-to-Consumer firms might exist.

H2: The relationship between social media network follower numbers and share return is stronger for Business-to-Consumer firms than for Business-to-Business firms.

To test this hypothesis, a dichotomous variable is created based on the firm's global industry classification standard (GICS) with Business-to-Consumer firms coded as 1 while the Business-to-Business firms are coded as 0. This variable, B2C is included in the regression analysis as well as its interactions with the three social media networks. The results are shown in Table 20 below.

TABLE 20 – AUTOREGRESSIVE MODEL - INTERACTIONS

VARIABLES	*CAR_CAPM*	Standard error
Facebook	-0.022	0.040
LinkedIn	-0.175**	0.071
Twitter	-0.597	0.381
Facebook#B2C	0.021	0.040
LinkedIn#B2C	0.161*	0.083
Twitter#B2C	-0.600	0.381
Earnings	-0.371	0.972
Leverage	-0.342	1.344
News	-0.000	0.002
Constant	0.554	0.341
Observations	1,255	
Number of firms	74	

*** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *Facebook#B2C* = Facebook-B2C interaction, *LinkedIn#B2C* = LinkedIn-B2C interaction, *Twitter#B2C* = Twitter-B2C interaction, *Earnings* = Return on assets, *News* = Coded 1 if a firm had firm specific news report, and 0 otherwise, *Leverage* = Debt to total assets.

Table 20 provides the results for the autoregressive fixed effects model, analysing the impact of the variables of interest on *CAR_CAPM*. *LinkedIn* is the only variable significant at the 5% level, while the LinkedIn-B2C (*LinkedIn#B2C*) interaction is marginally significant at the 10% level. It is noted that the B2C variable was omitted due to collinearity with the fixed effects dummy variable.

The null hypothesis is that there is no significant difference effect of the independent variables or the interactions of the independent variables on a firm's abnormal return. From the results above, we reject the null hypothesis for LinkedIn at the 5% level and for the LinkedIn-B2C (*LinkedIn#B2C*) interaction at a marginal 10% level. The null hypothesis is not rejected for the remaining variables. Thus we conclude that there is a statistically significant impact of a firm's Twitter follower numbers and cumulative abnormal return and a marginal statistically significant effect for the Twitter-B2C interaction on cumulative abnormal return.

From the analysis above and relevant to the objectives of this section it is observed that the outcome of the abnormal return variable does not depend on whether the firm has a consumer or business orientation at the 5% level.

4.7 CRITICAL MASS

Hypothesis 3a relates to a critical mass (turning point) and states:

H3a: There is an impact of social media network follower numbers on corporate value after a critical mass is reached.

To test Hypothesis 3a, the squared terms of the social media network follower number variables are included in the autoregressive model. With the coefficients of the statistically significant squared terms a potential cut off point (or critical mass exists) can be established.

Table 21 below provides the result and shows that no variable in this model is significant.

TABLE 21 – AUTOREGRESSIVE MODEL – SQUARED TERMS

VARIABLES	CAR_CAPM	Standard error
Facebook	0.002	0.002
LinkedIn	-0.008	0.054
Twitter	0.001	0.030
Facebook^2	-0.000	0.000
LinkedIn^2	-0.002	0.001
Twitter^2	-0.000	0.000
Earnings	-0.349	0.975
Leverage	-0.374	1.363
News	-0.000	0.002
Constant	0.401	0.358
Observations	1,255	
Number of firms	74	

*** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *Facebook*^{2} = squared term of Facebook, *LinkedIn*^{2} = squared term of LinkedIn, *Twitter*^{2} = squared term of Twitter, *Earnings* = Return on assets, *News* = Coded 1 if a firm had firm specific news report, and 0 otherwise, *Leverage* = Debt to total assets.

Table 21 provides the results for the autoregressive fixed effects model, analysing the impact of the variables of interest and their squared terms on *CAR_CAPM*. As displayed in the results above, none of the independent variables or the squared terms of the independent variables for Facebook, LinkedIn or Twitter are statistically significant. Thus the null hypothesis is not rejected and it is concluded that there is no significant correlation between the independent variables or their squared terms and the dependent variable. That is, the outcome of the cumulative abnormal return variable is not correlated with either Facebook, LinkedIn or Twitter. nor is there an effect present but the variables are non-linear. Based on prior research it was expected that a non-linear effect is present and the impact on cumulative abnormal returns changes at the turning point. However, the results do not provide evidence to that extent.

Given that neither the social media network followership variables nor the squared terms of those variables are statistically significant, no critical mass or turning point can be established.

4.8 SOCIAL MEDIA NETWORK RELATIONSHIP

Hypothesis 3b is proposed to investigate the difference between the three social media networks included in this study and is stated as follows:

H3b: The effect of social media network follower numbers on corporate value varies among Facebook, LinkedIn and Twitter.

A two-way and three-way ANOVA would have been suitable techniques to explore the difference between the social media networks. However, given the assumptions for ANOVA were violated and to the author's knowledge no *n*-way non-parametric version exists (where *n* is larger than 1), the following discussion is aimed at providing some insight into the differences between the social media networks.

The results in section 4.3 indicate that while no statistically significant correlation of the social media network follower numbers on cumulative abnormal return is detected, an effect is present for the social media network Twitter presence. Social media networks might differ due to an underlying factor. To examine whether there is an underlying factor present in the social media network follower numbers an exploratory factor analysis with varimax rotation is conducted. The rotated factor loadings matrix confirms that Facebook loads on both factors while LinkedIn and Twitter load on different factors.

TABLE 22 – PRINCIPAL COMPONENT FACTOR ANALYSIS WITH VARIMAX ROTATION

Factor analysis/correlation				Number of obs	1,329
Method: principal-component factors				Retained factors	2
Rotation: orthogonal varimax (Kaiser off)				Number of params	3

Factor	**Variance**	**Difference**	**Proportion**	**Cumulative**
CorpSocial	1.218	0.201	0.406	0.406
ConsumSocial	1.016	.	0.339	0.745

LR test: independent vs. saturated: chi2(3) = 72.43 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	***CorpSocial***	***ConsumSocial***	**Uniqueness**
Facebook	0.766	0.201	0.373
LinkedIn	0.796	-0.156	0.344
Twitter	0.007	0.976	0.048

Factor rotation matrix

	CorpSocial	*ConsumSocial*
CorpSocial	0.985	0.174
ConsumSocial	-0.174	0.985

Facebook = Total number of Facebook page ‘likes’ scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets.

The table gives the results for the principle component factor analysis with varimax rotation. For the factor analysis the three scaled social media network follower numbers were analyzed and two factors retained due to the eigenvalue of those factors being larger than one. The two factors account for 74.47% of the variance of the variables. The social media network follower variables used are scaled by total assets. Facebook loads both on *CorpSocial* as well as *ConsumSocial*, LinkedIn loads on *CorpSocial* while Twitter on *ConsumSocial*. The factor *CorpSocial* represents the more corporate and professional focused use of social media networks. This is based on the fact that on both networks, corporate details and additional information such as mission and vision are displayed. This indicates that firms use LinkedIn predominantly and Facebook to an extend to communicate the firm’s identity. The factor *ConsumSocial* represents the consumer orientated use of social media networks which is aligned with Facebook and

Twitter. Using the factors identified above an autoregressive model is run incorporating the *CorpSocial* factor and the *ConsumSocial* factor as independent variables.

TABLE 23 – RESULTS FOR AUTOREGRESSIVE MODEL – CORPSOCIAL, CONSUM-SOCIAL FACTORS

VARIABLES	CAR_CAPM	Standard error
CorpSocial	-0.303	1.79
ConsumSocial	0.017	0.05
Earnings	-0.357	0.37
News	-0.000	0.21
Size	-0.153	0.34
Constant	1.189	0.75
Observations	1,255	
Number of firms	74	

*** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CorpSocial* = factor representing corporate and professional focused use of social networks based on factor analysis, *ConsumSocial* = factor representing consumer orientated use of social networks based on factor analysis, *Earnings* = Return on assets, *News* = Coded 1 if a firm had firm specific news, and 0 otherwise, *Size* = Log of total assets.

The table provides the results for the autoregressive fixed effects model, analysing the impact of the variables of interest on *CAR_CAPM*. None of the coefficients in the model are significant at the 5% level. Specifically, neither of the factors *CorpSocial* and *ConsumSocial* are statistically significant, thus the null hypothesis is not rejected and it is concluded that there is no significant correlation between those factors and the dependent variable. That is, the outcome of the cumulative abnormal return variable is not correlated with neither *CorpSocial* nor *ConsumSocial* factors.

Based on the factor and regression analyses, it appears the social media network follower numbers represent two underlying factors namely *CorpSocial* and *ConsumSocial*. While no statistically significant impact could be detected for the two factors on cumulative abnormal return, it appears that there is a difference between the three social media networks.

4.9 FAMA FRENCH THREE-FACTORS AND CAPITAL ASSET PRICING MODEL

This section outlines the difference in results when using the Fama French three-factor model as opposed to the Capital Asset Pricing Model as the dependent variable.

TABLE 24 – RESULTS COMPARISON FOR AUTOREGRESSIVE MODEL

VARIABLES	*CAR_CAPM*	Standard error	*CAR_FF*	Standard error
Facebook	-0.001	0.000	-0.001	0.001
LinkedIn	-0.049	0.036	0.0672**	0.030
Twitter	-0.002	0.008	0.003	0.007
Earnings	-0.324	0.968	-0.296	0.586
News	-0.000	0.002	-0.002*	0.001
Size	-0.236	0.469	0.0928	0.291
Constant	2.178	1.641	-1.095	0.845
Observations	1,255		1255	
Number of firms	74		74	

*** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CAR_FF* = Cumulative Abnormal Return based on Fama French three-factor model, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, Earnings = Return on assets, *News* = Coded 1 if a firm had firm specific news, and 0 otherwise, *Size* = Log of total assets.

The table provides the results for the autoregressive fixed effects model, analysing the impact of the variables of interest on *CAR_CAPM* and *CAR_FF*. It appears from comparing the two methods to calculate cumulative abnormal return, the method using the Fama French three-factor model, produces statistical significance for the LinkedIn variable at the 5% level. Thus when using the Fama French three-factor model we can reject the null and conclude that LinkedIn follower numbers have an impact on cumulative abnormal return at the 5% level. However, provided the limitations of the Fama French factors as outlined in section 3.4, the interpretation of the results is potentially not reliable.

TABLE 25 – RESULTS COMPARISON FOR KRUSKAL-WALLIS EQUALITY-OF-POPULATIONS RANK TESTS

LargeSM	*CAR_CAPM*		*CAR_FF*	
	Large	**Small**	**Large**	**Small**
Observations	664	665	664	665
Rank Sum	431,788	451,998	423,684	460,102
chi-squared	1.952 with 1d.f.		6.530 with 1 d.f.	
probability	0.162		0.011	

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CAR_FF* = Cumulative Abnormal Return based on Fama French three-factor model, *LargeFb* = Coded 1 if a firm has a large Facebook presence, and 0 otherwise, *LargeLi* = Coded 1 if a firm has a large LinkedIn presence, and 0 otherwise, *LargeTw* = Coded 1 if a firm has a large Twitter presence, and 0 otherwise.

The table provides the results for the Kruskal-Wallis equality-of-populations rank tests for *LargeSM* on *CAR_CAPM* and *CAR_FF*. The overall social media network follower presence size has an impact on cumulative abnormal return when using the Fama French three-factor model, while it does not using the Capital Asset Pricing Model. The difference exists due to the additional factors included in the Fama French three-factor model. However, as outlined in section 3.3 some of this variation could potentially be due to the method of calculating the Fama French factors. Thus this study relies on the CAPM as the main model.

While a difference is detected for the overall social media network follower numbers, the statistically significant difference for the individual social media network follower numbers remains to be limited to the Twitter presence as presented in Table 26 below.

TABLE 26 – RESULTS COMPARISON FOR KRUSKAL-WALLIS EQUALITY-OF-POPULATIONS RANK TESTS

CAR_CAPM	***LargeFb***		***LargeLi***		***LargeTw***	
	Large	**Small**	**Large**	**Small**	**Large**	**Small**
Observations	647	682	664	665	664	665
Rank Sum	418,069	465,717	428,333	455,452	422,097	461,689
chi-squared	3.037 with 1d.f.		3.575 with 1 d.f.		7.741 with 1 d.f.	
probability	0.081		0.059		0.005	
CAR_FF	***LargeFb***		***LargeLi***		***LargeTw***	
	Large	**Small**	**Large**	**Small**	**Large**	**Small**
Observations	647	682	664	665	664	665
Rank Sum	420,603	463,182	431,683	452,102	417,519	466,266
chi-squared	1.905 with 1d.f.		1.993 with 1 d.f.		11.810 with 1 d.f.	
probability	0.168		0.158		0.001	

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CAR_FF* = Cumulative Abnormal Return based on Fama French three-factor model, *LargeFb* = Coded 1 if a firm has a large Facebook presence, and 0 otherwise, *LargeLi* = Coded 1 if a firm has a large LinkedIn presence, and 0 otherwise, *LargeTw* = Coded 1 if a firm has a large Twitter presence, and 0 otherwise.

The table provides the results for the Kruskal-Wallis equality-of-populations rank tests for *LargeFb, LargeLi* and *LargeTw* on *CAR_CAPM* and *CAR_FF*. The presence size on the social media network Twitter has a significant impact on cumulative abnormal return using either model. Hence the results reported in section 4.5 are supported.

This section has provided an insight into the implications when using different methods to calculate cumulative abnormal return. It appears that while there are differences utilising different approaches to calculate abnormal return, relying on the Fama French data is inappropriate due to the limitation outlined in section 3.4.

4.10 ASSUMPTION AND VARIABLE TESTS

This section provides for the tests performed to validate the assumptions underlying the analysis. The meaningfulness of the results is dependent on the validation of the assumptions and alternative techniques are used based on the results of the tests.

4.10.1 NORMALITY TESTS

TABLE 27 – SHAPIRO WILK W TEST FOR NORMAL DATA

Variable	Obs	W	V	z	Prob>z
CAR (CAPM)	1,329	0.974	21.292	7.66	0.000
CAR (FF)	1,329	0.970	24.704	8.033	0.000
CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CAR_FF* = Cumulative Abnormal Return based on Fama French three-factor model.					

The table presents the results for the Shapiro Wilk test for normal data for both *CAR_CAPM* and *CAR_FF*. Based on the results of the test the null hypothesis is rejected and it is concluded that the variables are not normally distributed. For ANOVA this requires the use of a non-parametric technique while for the regression this might influence the *p*-values and hence the detection of a correlation.

4.10.2 HETEROSCEDASTICITY TEST

To test whether the homoscedasticity assumption is violated a Wald test for groupwise heteroscedasticity is performed. A *p*-value of less than 0.05 level of significance indicates heteroscedasticity is present and a non-constant variance exists among the residuals.

Results of the modified Walt test are presented in Table 28 below.

TABLE 28 – MODIFIED WALD TEST FOR GROUP WISE HETEROSCEDASTICITY

H0: $\text{sigma}(i)^2 = \text{sigma}^2$ for all i	
chi2 (30)	= 63223.93
Prob>chi2	= 0.000

The resulting Prob>chi2 of 0.000 statistical significance level is an indication that heteroscedasticity is present. Given this violation of the regression assumption, we use a robust regression (Huber/White estimators).

4.10.3 HAUSMAN TEST

The Hausman test, as outlined in section 3.5.1.2 is used to decide whether a fixed effects or a random effects model is more appropriate.

TABLE 29 – HAUSMAN TEST (CAPM)

Variable	Coefficients (b) fixed	(B) random	(b-B) Difference	Sqrt(diag(V_b-V_B)) S.E.
Facebook	-0.001	-0.000	-0.001	0.000
LinkedIn	-0.024	0.000	-0.023	0.017
Twitter	-0.005	-0.000	-0.005	0.004

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic
chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 11.96
Prob>chi2 = 0.008

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets.

The table presents the result of the Hausman test in order to establish whether a fixed or random effects model are more appropriate for analysing the impact of social media network follower numbers on cumulative abnormal return using the CAPM. From the results above, we reject the null hypothesis and conclude that there is a significant difference between fixed effects and random effects estimators at the 5% level. Thus the fixed effects model is appropriate for the data and utilised in this study.

TABLE 30 – HAUSMAN TEST (FAMA FRENCH)

Variable	Coefficients (b) fixed	(B) random	(b-B) Difference	Sqrt(diag(V_b-V_B)) S.E.
Facebook	-0.001	-0.000	-0.001	0.003
LinkedIn	0.056	-0.000	0.056	0.131
Twitter	-0.004	-0.000	-0.004	0.003

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic
chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 21.48
Prob>chi2 = 0.000

CAR_FF = Cumulative Abnormal Return based on Fama French three-factor model, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets.

Results presented in Table 30 above for the Hausman test using the cumulative abnormal return based on the Fama French model further confirm the appropriateness of the fixed effects model.

4.10.4 TEST FOR AUTOCORRELATION

Autocorrelation can be present in time series data and hence this data set could be exposed. To detect autocorrelation, the Wooldridge test is performed and the results depicted in Table 31 below.

TABLE 31 – WOOLDRIDGE TEST FOR AUTOCORRELATION IN PANEL DATA

H0: no first order autocorrelation	
F(1,73)	= 140.989
Prob>F	= 0.000

From the results above, we reject the null hypothesis and conclude that there is first order autocorrelation in the idiosyncratic error term in a panel-data model at the 5% level. As a result, an autoregressive fixed effects model is used.

4.10.5 UNIT ROOT / STATIONARITY TESTS

Data stationarity is one of the assumptions underlying time series methods and hence is relevant to this study. The Fisher-type unit root test is employed to test this assumption and the result presented in Table 32.

TABLE 32 – FISHER-TYPE UNIT-ROOT TEST

Fisher-type unit-root test for *CAR_CAPM*
Based on augmented Dickey-Fuller tests

Ho: All panels contain unit roots	Number of panels = 74
Ha: At least one panel is stationary	Avg. number of periods = 17.96
AR parameter: Panel-specific	Asymptotics: T -> Infinity
Panel means: Included	Cross-sectional means removed
Time trend: Included	ADF regressions: 1 lag
Drift term: Not included	

		Statistic	**p-value**
Inverse chi-squared (148)	P	317.428	0.000
Inverse normal	Z	-7.136	0.000
Inverse logit t(374)	L*	-7.658	0.000
Modified inv. chi-squared	Pm	9.848	0.000

CAR_CAPM = Cumulative Abnormal Return based on CAPM

The table presents the results of the unit-root test for *CAR_CAPM*. From the results presented in Table 32 above, we reject the null hypothesis and conclude that there no unit root present in all panels, in other words, the data are stationary. Hence the stationarity assumption is not violated.

4.10.6 MULTICOLLINEARITY

Table 33 below depicts the variance Inflation factor (VIF) for the three independent variables. Given the factors for the independent variables are very close to 1, it is concluded that multicollinearity does not exist to a significant degree in the data set. This is based on the widely used rule of thumb that variance inflation factors with values of 10 or more indicate collinearity (O'Brien, 2007). Hence, the assumption of the independent variables being not correlated to a significant degree is not violated.

TABLE 33 – VARIANCE INFLATION FACTORS

Variable	VIF	1/VIF
Facebook	1.02	0.977
LinkedIn	1.02	0.978
Twitter	1	0.999
Mean VIF	1.02	

Facebook = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets.

4.11 ROBUSTNESS TESTS

The statistical tests outlined in 4.5 to 4.8 indicate limited significant effects, yet due to their specific statistical capabilities, do not provide detailed insights into the relationship between social media network activity and corporate value. The following panel data regressions seek to explore this relationship determine whether alternative methods produce similar results. Further robustness tests are conducted by replacing the social media network follower number variables with the factors established in section 4.8. The results for those tests are included in Appendix B.

Mixed OLS

Pooled or mixed ordinary least square regression is the most simplistic of the panel data regression analysis methods used in this study. Its limitations, as outlined in 3.4.2, are acknowledged and addressed by applying additional methods.

TABLE 34 – OLS REGRESSION

VARIABLES	*CAR_CAPM*	Standard Error
Facebook	-0.000*	0.000
LinkedIn	0.000	0.000
Twitter	-0.000***	0.000
Earnings	-0.042***	0.013
B2C	-0.001	0.002
Leverage	-0.021***	0.006
News	-0.003	0.003
Size	0.003***	0.001
Constant	-0.019***	0.007
Observations	1,329	
R-squared	0.030	

*** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *Facebook* = Total number of Facebook page 'likes'scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *B2C* = Coded 1 if a firm is a Business-to-Consumer firm based on global industry classification standard, and 0 otherwise, *Earnings* = Return on assets, *Leverage* = Debt to assets, *News* = Coded 1 if a firm had firm specific news report, and 0 otherwise, *Size* = Log of total assets.

Table 34 provides the results for the OLS regression model, analysing the impact of the variables of interest on *CAR_CAPM*. The variables *Twitter, Earnings, Leverage* and *Size* are significant at the 5% level and the variable *Facebook* is marginally significant at the 10% level. These results indicate that there is a significant relationship between those two and the dependent variable. That is the outcome of the cumulative abnormal return variable is associated with the social media network follower numbers for Twitter and, marginally, for Facebook.

Fixed Effects

Based on the result of the Hausman test a fixed effects model is confirmed and Table 35 below outlines the results for the fixed effects model.

TABLE 35 – FIXED EFFECTS MODEL

VARIABLES	*CAR_CAPM*	Standard error
Facebook	-0.001**	0.000
LinkedIn	-0.025	0.018
Twitter	-0.005	0.004
Earnings	-0.230	0.614
Leverage	-0.150	0.822
News	-0.002	0.003
Constant	0.327	0.437
Observations	1,329	
Number of firms	74	

*** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *Facebook* = Total number of Facebook page 'likes' scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *Earnings* = Return on assets, *Leverage* = Debt to assets, *News* = Coded 1 if a firm had firm specific news report, and 0 otherwise.

Table 35 provides the results for the fixed effects model, analysing the impact of the variables of interest on *CAR_CAPM*. Given that only the independent variable *Facebook* is significant at the 5% level, we reject the null hypothesis and conclude that there is a significant correlation between *Facebook* and the dependent variable. That is, the outcome of the cumulative abnormal return variable is correlated with Facebook follower numbers.

Given the outcome of the heteroscedasticity detected in the Wald in section 4.10.2, we use a robust regression (Huber/White estimators) and the results are presented in Table 36.

TABLE 36 – ROBUST FIXED EFFECTS MODEL

VARIABLES	*CAR_CAPM*	Standard error
Facebook	-0.001	0.001
LinkedIn	-0.025	0.034
Twitter	-0.005**	0.003
Earnings	-0.230	0.516
Leverage	-0.150	0.257
News	-0.002	0.003
Constant	0.327	0.333
Observations	1,329	
Number of firms	74	
R-squared	0.010	

*** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *Facebook* = Total number of Facebook page "likes" scaled by total assets, *LinkedIn* = Total number of LinkedIn page followers scaled by total assets, *Twitter* = Total number of Twitter page followers scaled by total assets, *Earnings* = Return on assets, *Leverage* = Debt to assets, *News* = Coded 1 if a firm had firm specific news, and 0 otherwise.

Table 36 provides the results for the fixed effects model with Huber/White estimators, analysing the impact of the variables of interest on *CAR_CAPM*. Only the *Twitter* variable is significant at the 5% level. From the results above, we reject the null hypothesis and conclude that there is a significant correlation between the Twitter and cumulative abnormal return. That is the outcome of the cumulative abnormal return variable is correlated with the social media network follower numbers for Twitter.

When taking into consideration the attributes of the data, the robust fixed effects model above is the most applicable alternative method to explore the relationship between social media network follower numbers and cumulative abnormal return. The results support the Kruskal-Wallis rank tests in section 4.5 with an effect displayed for Twitter. However, provided the autocorrelation detected in section 4.5, an interpretation of the LinkedIn relationship with corporate value is challenging. Further robustness testing outlined in appendix B provides further support for the results reported in this chapter.

4.12 CHAPTER CONCLUSION

This chapter reported the results for the empirical analyses performed based on the research design outlined in chapter three.

The data used for this study are reflected on in the sample characteristic and descriptive statistics section at the beginning of the chapter. The results for the four hypothesis are shown together with robustness tests. The chapter concludes with the test section outlining several violations of assumptions and outlining remedy techniques where appropriate. The next chapter provides conclusions regarding the hypotheses, and the implications this study has for theory and practice. It outlines the contributions made by this research, and discusses the study's limitations and directions for future research.

Chapter 5. DISCUSSION AND CONCLUSION

5.1 INTRODUCTION

The objective of this study is to add to the body of knowledge about the relationship between social media network activity and corporate value. A Social Media Value (SMV) model sketched a connection between three social media networks and their signals about three types of intangible assets: social and relationship capital, intellectual capital and human capital, which were proposed to link to corporate value. Specifically, the study observed social media network follower numbers and sought to establish whether those numbers correlated with corporate value. A further focus of the study is to explore whether the business focus and a social media network follower number turning point, or critical mass, impact corporate value. There is a lack of research of this kind in an Australian context and this study's objective is to contribute filling that gap. This chapter discusses the results for each of the hypotheses, outlines the implications of the study, its contribution, limitations, and scope for further research.

5.2 CONCLUSIONS ABOUT HYPOTHESES

Four hypotheses are advanced for testing and this section discusses each of the hypotheses and the results.

Hypotheses one is motivated by the lack of research in an Australian context and is presented as follows:

H1: The social media network follower numbers on Facebook, LinkedIn and Twitter impact the share return of firms.

This hypothesis is partially supported.

Through the results in section 4.5 this hypothesis is tested by initially establishing whether the social media network follower size overall, and on each individual social media network, had an effect on the cumulative abnormal return. The results show that the large social media presence on Twitter has a statistically significant effect on cumulative abnormal return and the large presences on Facebook and LinkedIn do as well, albeit those results are marginally significant at the 10% level. To further examine this relationship in more detail, an autoregressive fixed effects model was run but did not provide statistically significant results. The results confirm an impact on cumulative abnormal return for Twitter, yet not for Facebook and LinkedIn, and further relationships are not able to be established. Based on the results hypothesis one is partially supported.

Hypotheses two is based on prior research showing different levels of engagement with social media network following based on the industry a business operates in. Hence consideration is given that businesses focused on consumers might be different to businesses focused on other businesses and the following hypothesis is presented:

H2: The relationship between social media network follower numbers and share return is stronger for Business-to-Consumer firms than for Business-to-Business firms.

This hypothesis is not supported.

Results in section 4.6 show that there is no statistical difference between Business-to-Consumer firms and Business-to-Business firms nor for the interactions between the business classification and each of the social media network follower numbers. It is noted that the business classification B2C and LinkedIn interaction is marginally significant at the 10% level. Hence, based on the data for this study there is no difference in the effect on cumulative abnormal return when considering the business industry as specified by the Global Industry Classification Standard (GICS) at the 5% level. Thus hypothesis H2 is not supported.

H3a: There is an impact of social media network follower numbers on corporate value after a critical mass is reached.

This hypothesis is not supported.

Results in section 4.7 show that neither social media network follower numbers nor the squared term for those variables is significantly correlated with corporate value. There appears to be too much noise in the current data set to detect that relationship. As a result, the regression does neither support a relationship nor the consideration of non-linearity based on the data set. Non-linearity was expected in the data set as prior research had found a critical mass point where the correlation between social media network followers and corporate value changes from a negative coefficient to positive coefficient. Thus a critical mass or turning point is not established and H3a is not supported.

H3b: The effect of social media network follower numbers on corporate value varies among Facebook, LinkedIn and Twitter.

This hypothesis is partially supported.

The results in section 4.5 show that the social media presence on Twitter has a statistically significant effect on cumulative abnormal return while Facebook and LinkedIn do not at the 5% level. Further, the factor analysis in section 4.8 provides an insight into two underlying factors, a more corporate representation and a more consumer orientated social media focus. The three social media networks load differently on the two factors with both Facebook and LinkedIn loading strongly on the corporate social factor, while Twitter and to a lesser degree Facebook load on the consumer focused factor. This indicates a difference in three social media networks. However, further analysis did not detect what impact that difference has on cumulative abnormal return. The data do not provide for a more specific conclusion in regards to the impact on cumulative abnormal return and thus hypothesis 3b is partially supported.

5.3 IMPLICATIONS FOR THEORY AND PRACTICE

The findings of this study provide an insight into the relationship between social media network follower numbers and corporate value. The results advance the literature by contributing to the knowledge of the relationship between social media and corporate value. Social media network follower numbers provide a link, albeit not a very strong one, between social media and corporate value. For capital markets this points to a factor which through further research could be of importance for evaluating firms.

The findings compare with prior studies in adding to the understanding of the impact of social media network follower numbers on corporate value in Australia. Prior studies have found that the presence on social media impacts performance (Du & Jiang, 2015), the volume and sentiment of chatter on social media impacts performance (Luo et al., 2013; Tirunillai & Tellis, 2012), and social media network follower numbers impact performance in Spain and the United States (Paniagua & Sapena, 2014).

For practice, the study provides managers with an additional resource to refer to when discussing and evaluation the firm's investments into social media. As outlined in chapter one and chapter two, social media use is growing globally and businesses have an interest in utilising social media. Managers require a deeper understanding of social media opportunities and returns to allocate resources. The scope of studies in the marketing literature predominantly focuses on marketing-specific outcomes such as customer engagement, brand value and purchase intention, to name a few. There is a need for accounting focussed studies which study measures that link social media investments with financial performance. This study is part of a research program aimed at addressing that need and contributing to the literature.

While no specific critical mass could be established, the study concludes that social media network follower numbers do have an impact on corporate performance. While this impact has been established for Twitter but not for Facebook or LinkedIn, the identified future research opportunities could potentially close that gap. This study together with future research might enable business manager to make a more informed business decision when considering social media investments.

5.4 CONTRIBUTION

This study contributes to the literature by narrowing the gap in the understanding of how social media network activity correlate to corporate value. The current knowledge, based on Paniagua and Sapena (2014) is replicated and extended in an Australian context and hence provides an insight into this jurisdiction. For managers the study provides for some guidance on investments in social media. For educators, the study informs on the importance of social media's influence, an insight into social media networks and their impact on corporate value through shareholders' perception of the value of unrecognised intangible assets.

The lack of statistically significant results on the impact of social media network activity on corporate value suggests that too much noise is present in the model analysed. The research limitations and future research opportunities in the following sections provide for considerations on how limitations could be addressed and future research conducted to explore this relationship further and with more specific outcomes.

5.5 RESEARCH LIMITATIONS

Several limitations apply to this study and are opportunities for further research and refinement. The sample and observation length selected are recognised as limitations and by increasing the sample size, expanding industry sectors and extending the observation period, further insights can be gained.

This study focuses on social media network follower numbers and thus limits the extent of research. The independent variables used in this study are the social media network follower numbers. While beyond the scope of this master's thesis, further insights could be gained by expanding the scope to include further variables such as volume of interaction on social media networks, the sentiment of interactions and other social media variables. Other social media channels such as virtual worlds and blogs and their value effects could also be researched. Including posts and characteristics of posts into the analysis could also expand this study. The initiator of posts, the nature of posts and the reach of posts are some examples of potential extensions.

Independent and control variables could also be expanded and refined. For example, the social media investment by a firm could be included as a variable. Another extension could be to explore whether the share trading volume is impacted by social media network follower numbers.

This study examines the social media network activity across the three networks and their relationship with corporate value. Further research could be undertaken to establish the cost to increase / maintain social media network follower numbers and the relationship of those investments and corporate value. The insight gained would be to add to the understanding and hence focus on which investments yields the returns.

Firms in the sample are categorised as Business-to-Business and Business-to-Consumer firms based on the global industry classification standard (GICS), and belong in either the Consumer Discretionary, Consumer Staples, or Industrials groups. It is noted that a more detailed analysis of each individual firm's business environment might provide a different classification which might yield better insights. More retail-focused firms might benefit more from the use of social media than non-retail firms.

5.6 FUTURE RESEARCH

Further research could extend the scope of this study by increasing the scope of the independent variables, expanding the sample and observation period, the sample size as well as including further forms of social media. Additional insight could be derived by researching the effect of social media network follower numbers on specific future financial performance and ratios. Given the brand value signal impounded in the social media network follower numbers it is possible that the impact of this signal is on specific measures such as revenue, return on assets etc.

5.7 CHAPTER CONCLUSION

This study examines the relationship between social media network activity and corporate value. Social media network activity, specifically social media network follower numbers are examined and the link to corporate value considered. The social media value (SMV) model provides the theoretical link and several statistical methods are employed to test the hypotheses for this study.

This study finds some evidence of a relationship between social media network activity and corporate value. However, with the data available this study is not able to specify this relationship and further research is required to expand on this study.

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APPENDICES

APPENDIX A - SOCIAL MEDIA PRESENCE SIZE

The following tables provide further details on the sample. To arrive at an overall social presence size, the social media network follower numbers from each social media network are combined. Each profile is then categorised as large (1) for those profiles with total social media network follower numbers above the median and as small (0) otherwise. Similarly, for each of the social media networks the profiles were categorised as large (1) if the social media network follower number was larger than the median and small (0) if it was not.

Large Social Media Presence

Large	Freq.	Percent	Cum.
0	665	50.04	50.04
1	664	49.96	100
Total	**1,329**	**100**	

Large Facebook Presence

Large	Freq.	Percent	Cum.
0	682	51.32	51.32
1	647	48.68	100
Total	**1,329**	**100**	

Large Twitter Presence

Large	Freq.	Percent	Cum.
0	665	50.04	50.04
1	664	49.96	100
Total	**1,329**	**100**	

Large LinkedIn Presence

Large	Freq.	Percent	Cum.
0	665	50.04	50.04
1	664	49.96	100
Total	**1,329**	**100**	

APPENDIX B - REGRESSION USING *CORPSOCIAL* AND *CONSUMSOCIAL* FACTORS

Provided the factors established in section 4.8 it is possible that the replacement of the social media network follower numbers with those factors provides further insights into the relationship between social media activity and corporate value. The following section provides the results and discussion based on using the two factors in the relevant model for hypothesis one, two and three.

Hypothesis one

Following the results in section 4.5, an autoregressive fixed effects model is used to test whether the factors established in section 4.8 have an impact on cumulative abnormal return. The results are shown in Table B.1

Table B.1 Results for autoregressive model

VARIABLES	CAR_CAPM	Standard Error
CorpSocial	-0.303*	0.169
ConsumSocial	0.017	0.336
Earnings	-0.357	0.967
Leverage	-0.432	1.289
News	-0.000	0.002
Constant	0.241	0.29
N	1,255	

*** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CorpSocial* = factor representing corporate and professional focused use of social media networks based on factor analysis, *ConsumSocial* = factor representing consumer orientated use of social media networks based on factor analysis, *Leverage* = Debt to assets, *News* = Coded 1 if a firm had firm specific news, and 0 otherwise.

The above table provides the results for the autoregressive fixed effects model, analyzing the impact of the variables of interest on *CAR_CAPM*. None of the coefficients in the model are significant at the 5% level. The factor *CorpSocial* is marginally significant at the 10% level.

The results using the factors support the results in table 19 in that none of the variables is significant at the 5% level. Thus no statistically significant impact of the social media factors on corporate value has been detected in the data.

Hypothesis two

Following the results in section 4.6 an autoregressive fixed effects model is used to test whether the factors established in section 4.8 have an impact on cumulative abnormal return. The results are shown in Table B.2.

Table B.2 Results for autoregressive model

VARIABLES	CAR_CAPM	Standard Error
CorpSocial	0.818	1.722
ConsumSocial	11.053	7.489
CorpSocial#B2C	-1.046	1.731
ConsumSocial#B2C	-11.157	7.496
Earnings	-0.369	0.969
Leverage	-0.357	1.292
News	-0.000	0.002
Constant	1.136***	0.418
N	1,255	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CorpSocial* = factor representing corporate and professional focused use of social media networks based on factor analysis, *ConsumSocial* = factor representing consumer orientated use of social media networks based on factor analysis, *CorpSocial#B2C* = CorpSocial – B2C interaction, *ConsumSocial#B2C* = ConsumSocial – B2C interaction, *Earnings* = Return on assets, *Leverage* = Debt to total assets, *News* = Coded 1 if a firm had firm specific news, and 0 otherwise.

The table provides the results for the autoregressive fixed effects model, analyzing the impact of the variables of interest on *CAR_CAPM*. None of the coefficients for the independent variables in the model are significant at the 5% level. The constant of the model is significant at the 5% level.

The results using the factors to test hypothesis two supports the results in table 20 in that none of the variables is significant at the 5% level but the results do not support the results reported in table 20 at the 10% level. It is noted that using the scaled social media network follower numbers as tabulated in table 20 results in marginally significant interaction at the 10% for the *LinkedIn#B2C* interaction, this was not the case when using the factors. Thus, when using the factors *CorpSocial* and *ConsumSocial* we do not find the marginally significant result as reported in table 20.

Hypothesis three A

Following the results in section 4.7, an autoregressive fixed effects model is used to test whether the factors established in section 4.8 have an impact on cumulative abnormal return.

Table B.3 Autoregressive fixed effects model using factors

VARIABLES	CAR_CAPM	Standard Error
CorpSocial	-0.120	0.304
ConsumSocial	1.051	0.918
$CorpSocial^2$	-0.0593	0.044
$ConsumSocial^2$	-0.0720	0.063
Earnings	-0.360	0.971
Leverage	-0.439	1.321
News	-0.000	0.002
Constant	0.376	0.303
Observations	1,255	
Number of sec	74	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

CAR_CAPM = Cumulative Abnormal Return based on CAPM, *CorpSocial* = factor representing corporate and professional focused use of social media networks based on factor analysis, *ConsumSocial* = factor representing consumer orientated use of social media networks based on factor analysis, $CorpSocial^2$ = squared term of the variable CorpSocial, $ConsumSocial^2$ = squared term of the variable ConsumSocial, *Earnings* = Return on assets, *News* = Coded 1 if a firm had firm specific news, and 0 otherwise, *Size* = Log of total assets.

The above table provides the results for the autoregressive fixed effects model, analyzing the impact of the variables of interest and their squared terms on *CAR_CAPM*. No variable is statistically significant. Hence the analysis supports the findings for section 4.7.

The results using the factors supports the results in table 21 in that none of the variables is significant at the 5% level. Thus in comparison with section 4.7 no alternative conclusion can be reached using the two factors CorpSocial and ConsumSocial.

Conclusion

The results in this appendix are based on using the two factors established in section 4.8 to replace the social media network follower numbers. The tests for Hypothesis one, two and three are repeated using the two factors to test the results reported in chapter 4 for robustness. No additional significant insights were provided when using the factors *CorpSocial* and *ConsumSocial*. Thus the results reported in chapter 4 are supported by the results reported in this section.